Three Essays on Stock Market Dynamics

By

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ABSTRACT

This this dissertation aims to understand the comovements of international stock markets, financial contagion, and the relationship between international stock market comovements and macroeconomic factors. It contains three essays as follows:

The first essay investigates the common movements of stock market returns across the world and the regions. I employ a Bayesian dynamic latent factor model to decompose stock market returns into common world, regional, and idiosyncratic country-specific factors simultaneously. The results indicate that a common world factor is a significantly important source of the fluctuations for most stock markets, providing evidence of the international stock market comovements. I also find that the regional factor is another important reason for the fluctuations in emerging markets, but not in most developed markets. Persistence properties of the factors are examined to measure the adjusting speed to different shocks, and variance decomposition analysis is also performed to investigate the role of each factor in the volatility of stock markets. The roles of the world and regional factors, however, differ substantially across stock markets within different regions, as well as across developed and emerging markets. I reassess simple correlation analysis of bilateral linkages and find that although it can partially mimic actual stock market integration, this method provides an imperfect and biased depiction. In a partially integrated global economy, the degree of a market's comovement with international stock markets is closely related with that of its own country's economic integration in the world.

The second essay aims to investigate the linkage of Asian markets through the channel of stock market realized volatility. When examining the weekly realized stock market volatility in Asia, I find significant change of stock market volatility over time, especially in the financial crisis. Further, several different models, including simple pair-wise correlation model, DCC-GARCH model, and time-invariant and time-varying VAR model, are employed to investigate the volatility comovements in the main Asian stock markets. The empirical result shows that the correlations of stock market volatility among most of the Asian markets have increased after the crisis. The study also provides evidence that there is a contagion effect among the Asian markets during the crisis. Interestingly, from both the impulse response and variance decomposition analysis, the result shows that the Hong Kong market has a stronger impact on other Asian

markets than the Thailand market. The responses of other Asian markets to either the Hong Kong or Thailand market were greatly increased after the crisis. And from the variance decomposition analysis, it shows that the contribution to the variance of other Asian markets from either the Hong Kong or Thailand market both showed an increase during the crisis.

The third essay investigates the relationship between international stock market comovements and macroeconomic factors across a large group of countries over 1995-2009 in a global perspective. I use Bayesian dynamic factor models to decompose stock market prices and other major macroeconomic variables of 34 economies into common global factors and idiosyncratic country-specific factors. The result shows that the global factors account for a significant portion of an individual country's stock market volatility as well as its macroeconomic fluctuations. The global macroeconomic shocks have strong effects on the price movement of the global stock market as well as that of an individual market. And the result also indicates that a country's exposure to the global stock market risk can be largely explained by that country's exposure to the global macroeconomic risks.

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Chapter 1 Introduction

In recent decades, with the increasing global economic integration, understanding the cross-market linkages or international stock market comovements becomes central interest for financial academic researcher as well as policy makers. There is wide agreement among theoretical and empirical studies in the literature that provide evidences of the international stock market comovements, cross-market linkage, interdependence, and even financial contagion in financial crisis. In particular, there has been a rapid rise in the volume of cross-country capital flows, especially the capital flows into emerging market securities. Accurate specification of financial market linkage and understanding the underlying possible sources is of very importance in financial decisions, such as portfolio allocation, risk management for risk-averse investors, and other business decisions. Therefore, investigating the difference of financial market integration among developed and emerging markets in the world will provide insights of better understanding the global financial system. In particular, the new remunerative emerging markets have attracted the attention of international fund agents as an opportunity for portfolio diversification and have also intensified the curiosity of academics in exploring international market linkages. All these together raise interests to have further and detailed investigation of financial integration cross different markets in the world.

Financial literatures have already addressed many on the issues of the impacts of macroeconomic factors on stock markets. From multi-factors asset pricing models, any variables that can affect the future investment of the level of consumption could be price factor in equilibrium (see Merton, 1973; Breeden, 1979).Therefore, macroeconomic factors, which affect the returns of risky equity, need to be priced in a risk-averse economy (Ross, 1976). There are various financial theories and empirical studies that have investigated the relationship between macroeconomic factors and stock markets. Enhanced understanding the regularities and determinants of stock markets fluctuations is important for studies on financial markets and corporate finance; however, it is still in a blurred phase in understanding observable facts of the relationships between macroeconomic variables and stock markets. In particular, the more increased global economic and financial integrations, the more stock market linkages and interactions among different markets in the world exist, all together making it more complex to investigate the relationship between macroeconomic variables and international stock markets. Unfortunately, to my knowledge, there has not been any study investigating the relationships between stock markets and the underlying macroeconomic factors in a global perspective; effectively, the relationship between macroeconomic variables and stock markets cannot be modeled in isolation neither from the interaction of other markets nor the spillover effects of macroeconomic variables from other countries in the world. Especially, I am particularly interested in the link between stock market movements and the underlying macroeconomic factors in a perhaps partially integrated global economy. Therefore, of more interest in terms of understanding their relationship is to examine the link between international stock markets and macroeconomic factors in a global perspective.

Motivated by all these interesting issues of the comovements of international stock markets and their potential macroeconomic factors, in the first two essays I want to focus on the studies of the comovements of international stock markets, including investigation of the comovements of stock markets worldwide as well as regional simultaneously, and the financial contagion among Asian markets during the financial crisis. And the third essay aims to further investigate the relationship between macroeconomic factors and international stock markets in a global perspective, hence helping us to how an individual country's stock market simultaneously responds to the world business cycle shocks as well as its own macroeconomic fluctuations in a partially integrated world economy. Specifically, they are detailed as follows:

In Chapter 2, I aim to investigate the common movements of stock market returns across main markets in the world. I employ a Bayesian dynamic latent factor model to decompose the stock market returns into common world, regional and country-specific factors and estimate the model by using the Gibbs Sampling simulation. I investigate whether there exists some common global factor which can capture the comovements of stock market returns cross main countries in the world. I also examine whether there exist some common regional factors which are another important possible reasons for the fluctuations of stock market returns among different developed and emerging markets within different regions. Furthermore, the first-order autoregression analysis is employed to investigate their persistence properties of these factors to measure the speed of the adjustment to different shocks, and variance decomposition analysis is also performed to examine the role of each factor accounting for the volatility of stock market returns. And then I investigate the characteristics of international stock market comovements across different regions, as well as across developed and emerging markets. Further, I reassess simple correlation analysis of bilateral linkages and compare it with the method derived from the Bayesian factor model in this study on measuring bilateral stock market comovements. Lastly, I investigate the link between financial market integration and economic integration on the basis of the analysis in this paper. This essay fill the gap in the literature to investigate the international stock market comovements by estimating different factors simultaneously, including the common world, regional and idiosyncratic country-specific factors, especially the different characteristics of international stock market comovements across developed and emerging markets beyond what is implied by previous studies.

Furthermore, in Chapter 3, the essay aims to investigate to what degree there exist comovements amongst the main stock markets in Asia, especially the comovement of the stock market volatility beyond what is implied by previous literatures. I study the linkage of Asian markets through the channel of stock market volatility. By investigating the relationships of realized volatility indices of the main Asian markets, I apply four different models, including simple pair-wise correlation model, DCC-GARCH model, and time-invariant and time-varying VAR models, to study the stock market volatility comovements in the main Asian markets. I investigate whether the correlations among these main Asian markets have increased after the crisis, compared with those before the crisis. Hence, I can investigate whether there exist contagion effects among these main Asian markets during/after the crisis. Further, both impulse response and variance decomposition analyses are employed to investigate the transmission of the two main financial crisis sources in Asian markets, i.e. the Hong Kong and Thailand markets, before and after the crisis, respectively. The response analysis can help us to understand the responses of other Asian markets to the Hong Kong and Thailand markets in these two different periods. And variance decomposition analysis can help us to understand the contribution to the variance of other Asian markets from the Hong Kong and Thailand markets in the two different periods. The characteristics of the effects of the Hong Kong and Thailand markets on other Asian markets are examined, hence enhancing understating the impacts of two main financial sources on the Asian crisis.

In Chapter 4, the study aims to investigate the relationship between international stock market and underlying macroeconomic fundamentals across a large number of main countries over the period of 1995-2009. First of all, I investigate both international stock market comovements and economic integration by employing the Bayesian dynamic factor model to estimate the global factors, which capture the common movements across countries in the world. Secondly, I perform two different VAR analyses with a detailed examination of the relationships between international stock markets and macroeconomic fundamentals. Further, variance decomposition analysis is employed to investigate the different impacts of global and country macroeconomic factors on the fluctuations of international stock markets. Lastly, I investigate to what extent the degree of the comovements of international stock markets reflects the degree of global economic integration. Therefore, I use the variance shares of global factor for international stock markets estimated as dependent variable and estimate a pooled-sectional regression on the variance shares of global macroeconomic variables. All this aims to investigate the relationship between a country's exposure to the global stock market risk and that country's exposure to the global macroeconomic factors.

Chapter 2 Understanding the Comovements of International Stock Markets

2.1 Introduction

With increased economic globalization in recent decades, there has been a rapid rise in cross-economy capital flows, especially into emerging markets. All these have accelerated financial market linkages across countries in the world. There is a wide agreement among theoretical and empirical studies on financial market integrations that provide evidence of the comovements of international stock markets. In the literature, there are a wide variety of studies of cross-market linkages and interdependence, spillover effect from one market to others, and common factors across the globe (Forbes and Figobon, 2002; Hamao et al, 1990; Brooks and Del Negro, 2005, among others).

Studies of international stock market comovements can be realized through measure of the correlation coefficients, providing evidence of cross-market linkages and relationships on the basis of correlation analysis.[1] In earlier studies of international market linkages, Hamao et al. (1990), Koch and Koch (1991), and Longin and Solnik (1995), among others, exploit sophisticated econometric techniques to measure cross-market correlations, providing evidence of significant cross-market linkages in the world.[2] Studies of cross-market correlations have been boosted in recent decades due to the frequent crises in emerging markets. Financial crises, which result in the significantly increased correlation across markets, are generally referred to "contagion" (Boyer et al., 1999; Loretan et al., 2000; and Forbes and Figobon, 2002, among

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1 Based on the notion which describes a phenomenon of a market (or asset price) "moving with" another market (asset price, respectively), comovements can be defined as a pattern of positive correlation (Barberis et al., 2005). Therefore, the correlation analysis can be used to investigate the phenomenon of stock market comovements.

2 Among other much earlier studies, see Levy and Sarnat (1970), Solnik (1974), Eun and Shim (1989), Lin, et al. (1994), Janakiramanan and Lamba (1998).

others). They find that there is an increase in correlation coefficients, conditional on stock market volatility, when there is a high level of stock market comovements.

Studies of international stock market comovements can also be measured via investigation of the common factors among markets. Previous studies of common factors show the comovements across stock markets, indicating either the world effects on all markets, or the regional effects across a group of markets within some specific region (Fama and French, 1995; Bodurtha et al., 1995; Richards, 1995; Barberis et al., 2005; Corsetti, et al., 2005; and Beltratti and Morana, 2008, among others). This provides evidence of common fluctuations across the markets they studied. In particular, a few of them have shown some strong common trends for geographically financial integration among the markets in the same region. For example, Ng (2000) uses the aggregate price indices to examine the effects of Japan and the U.S. on six Pacific-Basin equity markets, and finds that Japan as a regional factor and the U.S. as a world factor are important for the markets in the region. Mapa and Briones (2006) investigate a group of Asian-Pacific stock markets and find that common components significantly explain the national stock market returns in this region. However, Pukthuanthong and Roll (2009) show that the correlation analysis employed by many previous studies to measure the broad cross-market integration, has been found to poorly mimic other measures of the actual integration. Thus, they derive a new integration measure based on the more explanatory power of a multi-factor model to investigate global integration via principal components.

In sum, what is common in all previous studies of the comovements of international stock market is that they are not studies of world, regional and idiosyncratic country-specific factors simultaneously.[3] In particular, among the studies of the correlation between stock markets, most only examine bilateral correlation, which provides an imperfect and biased empirical depiction of actual market integration (Pukthuanthong and Roll, 2009). Furthermore, data limitation and

3 Several similar studies of stock market returns comovements employ the latent factor approaches that are probably closer to the methods in my study. However, their focus is on individual firms' stock returns. For example, Brooks and Negro (2005) use the latent factor model to decompose the international stock returns into global, country, and industry components. Bekaert, et al. (2009) develop time-varying factor model and decompose the country-style individual portfolios into global and regional factors, potentially capturing the world market integration or regional integration. Heston and Rouwenhorst (1994) investigate the individual firms in 12 European markets and decompose international returns into region effects, within-region country effects and also industry effects.

econometric intractability have heretofore limited attention to either a few stock markets or only a small group of stock markets within some special region, such as Asia, South America, or Europe. There has not been a comprehensive and detailed study regarding how and to what extent the fluctuations across stock markets are associated with the worldwide, regional, and country-specific shocks simultaneously. Under a partial economic global integration economy as well as geographically regional integration economy, we not only contend that financial market development could be globally integrated, but also to some degree, it could be geographically regionally integrated for their increasingly more regional economic cooperation and financial cooperation among economies within the same region. Therefore, I argue that it would be more reliable and subsequently imperative to distinguish between world and regional effects.

In this study, I aim to address these and related issues by employing a Bayesian dynamic latent factor model to estimate common factors of stock market returns in a group of 34 economies covering several regions in the world. Specifically, I aim to simultaneously uncover worldwide comovements among international stock markets, regional factors across a subgroup of markets within the same region, and idiosyncratic country factors for individual countries. I also investigate the characteristics and differences among developed and emerging markets, which are beyond what has been implied by previous studies. Furthermore, I reassess how simple correlation analysis, a widely used measure of bilateral market linkages, can mimic the measure of stock market comovements on the basis of the Bayesian dynamic factor analysis. Lastly, I explore the relationship between market comovements and real economic integration in a partially integrated global economy.

The study has several important implications for financial literature. First of all, we can better capture the common movements for all of the global markets or only for the markets within a region, because the method can investigate a large group of markets simultaneously instead of through bilateral market correlation. No representative stock market is needed. Further, the framework of the dynamic factor model allows us to separate the world and regional factors, and thus it can help us to investigate the pure different factor's effects, so as to not mix up the regional effects with global effect if we studied only the global or regional factor or if we used the VAR model or others. It can help us to better separately uncover common movements across the world as well as among a specific subgroup of regional markets. For example, when studying only a group of stock markets in Europe, it may lead one to believe that observed comovements are particular to the European stock markets. In fact, the result in this study shows that those so-called comovements among the European stock markets are actually mainly due to worldwide movements, instead of regional factor in many previous studies. Similarly, when studying only a group of stock markets in Asia, we can also find there are strong comovements among the Asian stock markets. However, the result in my study demonstrates that the observed comovements in Asia are actually partially due to worldwide movements, and also partially due to regional movements specific to the region of Asia. Thus, this study can help identify and distinguish the differences of international stock market comovements across different regions. Lastly, through this framework, we can collate the dynamics of factors with historical stock market fluctuations over decades, and also investigate the persistence properties of international stock markets.

The remainder of the study is organized as follows: Section 2.2 defines the model and statistics procedures; Section 2.3 describes the data used in my study; Section 2.4 presents major empirical results on the basis of Bayesian dynamic factor analyses; Section 2.5 reassesses simple correlation analysis of bilateral linkages; Section 2.6 examines the link between market integration and real economic integration; and the final section summarizes the findings.

2.2 Empirical methodology

In this study, I employ a Bayesian dynamic latent factor model to estimate the common dynamic factors across 34 stock markets covering 6 regions in the world. Specifically, the following factors are estimated simultaneously in this study: (1) A dynamic factor common to all the stock markets (world factor); (2) A set of regional dynamic factors only common to the markets within each specific region, but not common outside the region;[4] (3) 34 different idiosyncratic country-specific factors to capture dynamic influences for each individual market due to its own idiosyncratic dynamic characteristics.

4 The study includes 6 main regions in the world: Oceanian Developed, Asian Developed, Asian Emerging, European Developed, North America Developed and South America Emerging.

As in the latent factor model literature (Cho, et al, 1986), these factors are unobserved. However, borrowing from the identified vector autoregression (VAR) in stock market comovements (Eun and Shim, 1989; and Forbes and Rigobon, 2002, among others), structural VAR (SVAR) to analyze the volatility or disturbance by breaking it into several sections (Engsted and Tanggaard, 2002; and Chow and Kim, 2003, among others), and also the dynamic latent factor model in investigating the firms' stock return comovements (Brooks and Del Negro, 2005; and Bekaert, et al. 2009, among others), we can identify these factors simultaneously by imposing restrictions on the factor exposures of markets in the world.

The model is built on several assumptions. First, I assume that aggregate stock market returns could be decomposed into world, regional, and idiosyncratic country-specific factors. The world factor represents the global shock to all of the international stock markets. A typical example of global shocks is the recent 2007-2009 global financial crisis causing the global financial contagion. The regional factor, similarly, embodies the shock only to the markets within the same region simultaneously but is relatively innocuous to the markets outside, while the country-specific factor represents the idiosyncratic effect on each individual market due to its own structure and characteristics. Furthermore, these factors are assumed to be contemporaneously uncorrelated. This assumption is necessary for the model to be identifiable. Both the world and regional factors have different effects on individual markets, as indicated by different factor coefficients.

Therefore, in this study there are 7 common dynamic and unobserved factors designed to characterize the temporal comovements of international stock markets. Let N denote the number of markets, and T the length of time series. Observable variables of stock market returns are denoted $R_{i,t}$, for i=1,…,N, and t=1,…,T. There are two main types of dynamic factors I want to identify in this study, i.e. factor f_t^{world} and regional factors $f_{r,t}^{region}$ (where r=1,2,…,R (R=6)).[5] Thus for country *i*, the specification of factor model can be written as:

5 Here r=1,2,…,R (R=6); and one each for developed markets in Oceania, developed markets in Asia, emerging markets in Asia, developed markets in Europe, developed markets in North America, and emerging markets in South America, respectively.

$$R_{i,t} = \mu_i + b_i^{world} f_t^{world} + b_i^{region} f_{r,t}^{region} + \varepsilon_{i,t} \tag{2.1}$$

Where *i* refers to the country, *t* to month; $R_{i,t}$ represents the stock market returns; μ_i is the expected excess stock returns at country i; f_t^{world} represents the world factor for all stock markets; $f_{r,t}^{region}$ represents the different regional factor if market *i* belongs to region r (r=1, 2…, R); and $\varepsilon_{i,t}$ represents the idiosyncratic country-specific shock to each individual market i, all in month t.

In this model, idiosyncratic country-specific factors are assumed to be normally distributed, but may be serially correlated. They follow p-order autoregression:

$$\varepsilon_{i,t} = \psi_{i,1}\varepsilon_{i,t-1} + \psi_{i,2}\varepsilon_{i,t-2} + ... + \psi_{i,p}\varepsilon_{i,p} + u_{i,t} \tag{2.2}$$

Where $Eu_{i,t}u_{j,t-s} = \sigma_i^2$ for i = j and s = 0, 0 otherwise.

The evolution of the world factor and regional factors is also assumed to be governed by an autoregression of p-order with normal errors.

$$f_t^{world} = \phi_1^{world} f_{t-1}^{world} + \phi_2^{world} f_{t-2}^{world} + ... + \phi_t^{world} f_{t-p}^{world} + u_t^{world} \tag{2.3}$$

$$f_{r,t}^{region} = \phi_{r,1}^{region} f_{r,t-1}^{region} + \phi_{r,2}^{region} f_{r,t-2}^{region} + ... + \phi_{r,p}^{region} f_{r,p}^{region} + u_{r,t}^{region} \tag{2.4}$$

Where

$$Eu_t^{world}u_t^{world} = \sigma_w^2; \quad Eu_{r,t}^{region}u_{r,t}^{region} = \sigma_{region,r}^2;$$

and $Eu_t^{world}u_{r,t}^{region} = 0; Eu_t^{world}u_{r,t-s}^{region} = 0; Eu_{r,t}^{region}u_{r,t-s}^{region} = 0$ for all r, and all s≠0.

Here all the corresponding innovations, u_t^{world} and $u_{r,t}^{region}$, r=1,…,R and $u_{i,t}$, i=1,…,N, are assumed to be zero mean, contemporaneously uncorrelated normal random variables.

With these assumptions, I can stack the above equation (2.1) into following forms:

$$R_t = \mu + Bf_t + \varepsilon_t \tag{2.5}$$

Where R_t denotes the N×1 vector of stock market returns and $R_t = [R_{1,t}, R_{2,t}, ..., R_{n,t}]^{'}$, denotes the K×1 vector of dynamic factors (K=7) and $f_t = [f_t^{world}, f_{1,t}^{region}, f_{2,t}^{region}, f_{3,t}^{region}, f_{4,t}^{region}, f_{5,t}^{region}]^{'}$, B is a N×K coefficients matrix of b's, and ε_t denotes the N×1 vector of idiosyncratic shocks for different markets. And similarly, $u_{f,t} = [u_t^{world}, u_{1,t}^{region}, u_{2,t}^{region}, ..., u_{R,t}^{region}]^{'}$ where $u_{f,t} \sim N(0, Q)$ and Q is a diagonal variance-covariance matrix.

The econometric model employed in this study aims to derive the conditional distribution of dynamic factors given prior parameters. In this model, the factors are unobservable, so I employ the Gibbs sampling simulation on the basis of the Bayesian method of data augmentation to extract the estimates of unobserved factors in this study. There are two related identification problems in the model (2.1)-(2.4) that should be noted here. Neither the signs nor the scales of the factors and the factor coefficients are identified separately. Therefore, first of all, the signs are identified by requiring one of the coefficients for each factor to be positive. I follow the method in Kose et al. (2003) to restrict the factor coefficients of the world factor for Australia and the factor coefficients of regional factors for Australia, Hong Kong, Korea, the United Kingdom, Canada, and Argentina to be positive. Secondly, the scales are identified by following Sargent and Sims (1977) and Stock and Watson (1989, 1993) to assume that each variance of $u_{f,t}$ is equal to a constant. Here I follow the convention by normalizing the variance of $u_{f,t}$ to be unity.

Thus all comovements are mediated by the common factors, which in turn all have the autoregressive representations. Through this analysis, we are able to simultaneously examine the world, regional and country-specific impacts on international stock markets. Since the dynamic factors are not observable, analysis of the systems could not be straightforward as the general econometrics regressions suggest. In the conventional method, a state space model can be estimated by using the Kalman filter to derive sample log likelihood function conditional on the unknown parameters. In the likelihood function, it is maximized numerically with respect to the parameters until convergence, in order to extract all these parameters. However, in my study, with a large number of factors in the state equation, the Kalman filter can become computationally rather burdensome. Therefore, in this study I use the method of Markov Chain Monte Carlo (MCMC) to estimate the posterior distribution of unobserved factors and the parameters. MCMC has been widely used by Kim and Nelson (1999) and Aguilar and West (2000), among others, to estimate the factors. The setup is a dynamic factor model where each level admits a state-space representation. In this study, I take advantage of Bayesian Gibbs sampling procedure allowing us to estimate a large cross-section state space system with a large number of unknown factors and parameters. The main idea of this method is to determine the posterior distributions for all unobserved factors given the observable data and other parameters, and then to determine the posterior distributions for all unknown parameters condition on the dynamic factors and observable data. All of the joint posterior distribution for all unobservable factors and unknown parameters can be drawn by using the MCMC procedures on the full set of conditional distributions.

In this implementation in this study, for simplicity and also for saving the degree of freedom, I assume that the lengths of all factor autoregressive polynomials are 1. It should be noted that the model, in principle, works well for the general case of AR(*p*) autoregression. In Bayesian econometrics, unknown parameters are usually treated as random variables followed by underlying stochastic distribution, and the prior on all factor distribution is N(0,1). Given appropriate prior distributions and arbitrary starting values for the model's parameters, Gibbs-sampling can be implemented by successive iteration of the following three steps: Firstly, I generate the posterior distribution of the factors conditional on all the stock market returns data and all the prior parameters of the model, including: draw world factor conditional on the prior parameters and regional factors; and then draw each regional factor conditional on the world factor and prior parameters. Secondly, I generate the parameters ϕ from the conditional distribution conditional on the dynamic factors. Thirdly, I generate ψ_i , b_i , σ_i^2 based on the equations (2.1) and (2.2) conditional on the dynamic factor and the returns data for the i-th stock market. Step 2 and step 3 are carried out by using independent Normal-Gamma priors.

All the steps are iterated S times, in which the first S_1 draws are discarded as burning-in replications to remove the effect of initial values. Under the regularity conditions satisfied here, we can produce the convergence of the Markov Chains and generate the parameters and the unobserved factors. The detail procedures can be found in Appendix A.

2.3 Data description

In this essay, I investigate a group of main 34 stock markets in the world from January 1993 through December 2009.[6] [7] All national stock price indices are the closed observations of market prices expressed in local currency from Datastream International.

<Table 2.1 here>

Table 2.1 shows the countries and regions included in this study, and also presents the definition of the markets in same region. In this study, I follow the MCSI Criteria to classify different markets into developed and emerging markets. Based on the criterion of geographical closeness, market developments and interactions, international stock markets in this study are classified into 6 different regions. [8]

I follow the conventional way to calculate the monthly stock market returns for country *i*, i.e.

$$R_{i,t} = 100 * (\log p_{i,t} - \log p_{i,t-1}) \tag{2.6}$$

Where *i*: stock market 1,2,..,N; *t*: month 1,2,…,T; $R_{i,t}$ represents the stock market returns; $p_{i,t}$ is the stock price index in local currency. Instead of choosing the price index $p_{i,t}$ in a fixed date as monthly price for stock market, here I use the average of price index in order to eliminate the excess volatilities of price. These average price benchmarks are measured by applying the average price index in all trading dates in each entire month.

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[6] The detail of national stock market indices included in this study can be found in Table 2.1 in Appendix B.

7 Some stock markets are not included in this study for the data is not available from the start date of January, 1993.

8 The details can be found in Table 2.1 in Appendix.

One concern with the procedure is whether big stock markets may have more power in affecting the world factor or regional factor just because of the big size of its market. In this study, I use stock market returns, which actually are the changing rate of stock price index, so the size of stock market can have no direct impact on this study of international stock market comovements. The way I follow in this study is to ensure that all the series have equal weight irrespective of its relative market size in the world.

2.4 Empirical results

In order for this empirical analysis to be conducted, it is attempted in numerous ways. First, the initial values are checked to see if they would affect the results. Random values are used repeatedly as the initial parameters to simulate the results. Within these parameters, the procedure always came to the same results across the repetition. Additionally, the simulation is iterated in different lengths, ranging from 5,000 to 30,000. As the Gibbs sampler converges to the same results if the iteration is greater than 5,000, for this study, this Gibbs sampler is iterated 20,000 times, of which the first 5,000 are discarded as burn-in replications.

2.4.1 The dynamic factors

In this section, the Bayesian dynamic latent factor model is employed to estimate the set of dynamic factors designed to measure the comovements across the markets in the world, as well as within each region. The main objective is to investigate whether the dynamics of world factor could reveal main financial crises or events across global markets. Further, the objective aims to examine whether regional factors could exhibit ups and downs across the stock markets within each region. With this in mind, the country-specific factors are then studied to determine whether these factors are able to reflect the idiosyncratic dynamics of each individual market.

<Figure 2.1 here>

Figure 2.1 illustrates the median of the posterior distribution of world factor for stock markets in the world, along with the 5 percent and 95 percent quantiles. The narrowness of three

different bands to represent the estimation of world factor is quite precise. As shown in Figure 2.1, the dynamics of world factor accurately describe the major known global market shocks and crises over the past two decades.

Among them, several significant troughs exist that characterize the major global markets shocks. For example, the Mexico 1994-1995 Financial Crisis influenced most markets in South America, and subsequently, other markets throughout the world. Take also the Asian Financial Crisis, which began in July 1997. This crisis eventually raised the fears of worldwide markets meltdown due to financial contagion. Another significant event that impacted most stock markets in industrialized economies was the so-called IT bubble, which started in early 2000 in the United States. Next, the stock market downturn in 2001 was closely tied with the September 11 attacks as investors became unsure about the prospect of terrorism affecting the future economies. After recovering from the lows reached during the September 11 attacks, the subsequent stock market downturn of 2002 started in May of that year, with dramatic declines in July and September leading to new economic lows across a large group of countries including the United States, Canada, Asia, and Europe. Most recently, the stock markets crash that took place over 2007 to 2009 had a deleterious impact across the globe. The latter is arguably the most disastrous financial crisis in recent history. The steepest drops of factor dynamics in Figure 2.1 coincide with the disastrous market downturn of 2008 across the world.

<Figures 2.2.1--2.2.3 here>

Figures 2.2.1 through 2.2.3 illustrate the medians of the posterior distributions of regional factors for stock markets in the regions of Asia (emerging), Europe, and South America respectively, along with 5 percent and 95 percent quantiles. The Asian (emerging) regional factor is presented in Figure 2.2.1. It is worthwhile to note that as shown in this figure, the pattern of common movements in Southeast Asia coincides with the fluctuations of emerging markets within the region. Through Figure 2.1, it is evident that there were several significant peaks and troughs that have occurred over the past 20 years. Take for example the peak in December 1993 and the trough in January 1994. These fluctuations can be explained by the fact that a wide variety of investments around the world were funneled into the Southeast Asia economies. Thus, in late 1993, the market reached "Bull market" status, then turned to a "Bear market" in early

1994. Other big downturns within this region in February 1998 and May 1999 are linked with the 1997-1998 Asian financial crises, the 1998 Russian financial crisis, and the 1999 financial crisis in Argentina.

The regional factor for the developed markets in Europe is presented in Figure 2.2.2. In this figure, it is evident that regional factor is less volatile, despite two major troughs in September 1998 and in September 2001. The first trough can be attributed to the Russian financial crisis in August 1998. Here, the Russia commodities trade was greatly dependent on the export of raw materials such as Petroleum, natural gas, metals, and timber. The Russian crisis also impacted European and Latin American countries. The second trough can be explained by the market downturn in 2001, resulting from the panic among global capital investors after the September 11 attacks.

Figure 2.2.3 clearly shows that the regional factor of South America is much more fluctuated than other regional factors. The pattern of its movement is closely tied to the fluctuations of the emerging markets within this region. Several significant peaks and troughs coincide with major regional market fluctuations over the last 20 years, such as the 1994 Mexico financial crises, which impacted the Latin America markets. The second severe drop was in August 1998, followed by a third in early 1999. The latter was a result of Brazil's financial crisis, which occurred after the stock market plunged and currency depreciated in several Latin American countries. It should be noted that Figure 2.2.3 also shows that the regional factor is more volatile in former periods than latter periods, which is mainly attributable to the semi-frequent market crashes and economic crises across this region.

2.4.2 Difference of the trends among emerging and developed markets

Here, the dynamic trends of stock market returns are investigated among some typical emerging and developed markets. Furthermore, in order to gain more insights into how world factor and other various factors interact, the comparisons among world factor, regional factor, and the dynamics of actual stock market returns in several selected markets are examined in detail. Specifically, the markets examined are those of the United States, Thailand, the United Kingdom, and Argentina. To make the scales more comparable, the medians of the factors are multiplied by their respective median factor loadings in the markets returns equation. The results for these 4 markets are presented in Figures 2.3.1-2.3.4.

<Figures 2.3.1-2.3.4 here>

Figure 2.3.1 displays the United States actual stock market returns, along with the median of world and North American regional factors. World factor is consistent with most of the major stock market crises and booming periods. Compared with world factor, regional factor has a relatively small portion of stock market returns. Interestingly, the United States stock market returns and world factor exhibit some common movements especially in the recent 15 years. The correlation between the median world factor and the United States stock market returns is 0.892, which indicates that the dynamics of the United States stock market are a strong representation of the common fluctuations of global stock markets. This is why a wide variety of studies in the literature employ the United States market as a proxy of exogenous shocks to global stock markets. However, there are still some notable differences between the world factor and United States stock market. World factor shows a relatively more volatile movement during the period of 1993 to 1995, whereas the United States stock market returns are less volatile, even with some contrary movement. The volatility of the world factor is, to some extent, due to the flow of refugee capital into East Asian developing countries, as well as financial crises in South America.

The Thailand actual stock market returns, along with the median of world and Asian (emerging) regional factors are displayed in Figure 2.3.2. Regional factor is consistent with most peaks and troughs of the Thailand stock market returns. Compared with the other two markets, regional factor accounts for a larger portion of stock market fluctuations in Thailand. In particular, during the Asian crises, regional factor explains a larger part than world factor, indicating that Thailand stock market is more influenced by the regional shocks than world shocks during these crises.

Figure 2.3.3 presents the United Kingdom actual stock market returns, with the median of median and European regional factors. From this figure, it is clear that world factor is also consistent with most peaks and troughs of stock market returns in United Kingdom. Interestingly, the movement of stock market returns in the United Kingdom is very similar with that of United States. The stock market returns and world factor exhibit the most similarity of common movements over the last two decades. Compared with the world factor which captures most portions of the market returns, regional factor has very little to negligible impact on the stock market fluctuations in most periods.

In a similar vein, Figure 2.3.4 illustrates the Argentinean actual stock market returns along with the median of world and South American regional factors. In Argentinean stock market, regional factor is more consistent with most of the peaks and troughs of the stock market returns rather than those in world factor. Compared with world factor, regional factor is able to account for a larger portion of the stock market fluctuations in this country. In particular, during several regional financial crises in South America, regional factor successfully captures the stock market fluctuations, and reflects strong regional stock market comovements in this region.

Through all of the abovementioned figures, the results suggest that there are worldwide, regional and country-specific sources of shocks to stock markets. They play different roles in driving the fluctuations of stock market at different periods across markets. In emerging markets, regional factor may be more strongly reflective of actual stock market returns. On the contrast, in developed markets, world factor accounts for a substantial fraction of the fluctuations of stock market returns, which implies the common worldwide movements embodied in these stock markets.

Other important regularities are also clearly indicated by these figures. First of all, the return fluctuations of emerging markets are more volatile than in developed markets, such as the markets in Thailand and Argentina. Furthermore, world factor generally captures more fractions of stock market fluctuations in developed markets such as in the United States and the United Kingdom markets, whereas regional factor most likely captures more among some emerging markets, such as in Thailand and Argentina.

2.4.3 Persistence properties of the dynamic factors

Are common dynamic factors persistent, or any of idiosyncratic country-specific factors are more persistent than other? A necessary investigation of the persistence properties will help to understand the insight of adjustment speeds. Here, persistence property is considered as a measure of adjusting speeds to different shocks. Thus, this section aims to assess the persistence properties of dynamic factors in the investigation of different characteristics of shocks to stock markets.

To measure persistence, the coefficient of first order autocorrelation is calculated as follows::

$$f_{k,t} = \phi_{k,1} f_{k,t-1} + u_{k,t} \tag{2.7}$$

and

$$\varepsilon_{i,t} = \phi_{i,1}\varepsilon_{i,t-1} + u_{i,t} \tag{2.8}$$

Based on these equations, it is possible to measure the persistence of different shocks over the last two decades by analyzing the autocorrelation coefficients of different factors, including world, regional and country-specific factors. The medians of first order autocorrelation for world and regional factors are reported in Table 2.2, and country-specific factors are reported in Table 2.3. The larger coefficients represent the higher degrees of their persistence, implying the longer impacts of its past shocks. Thus, the persistence properties of factors can be used as an indicator of adjustment speed.

<Tables 2.2 and 2.3 here>

As shown in Tables 2.2 and 2.3, the results indicate that world factor has relatively larger and positive autocorrelation of 0.371. The coefficients of first order autocorrelations for regional factors are 0.243, 0.289, 0.437, 0.310, 0.220, and 0.234 for the Oceania, Asia (developed), Asia (emerging), Europe, North America, and South America, respectively. Compared with five other coefficients, the persistence of the Southeast Asian regional factor is the most persistent. The coefficient is 0.437, indicating that the adjustment to regional shocks is slow for the stock markets in this region. The other four coefficients are relatively close, ranging from 0.22 to 0.31. The smallest one is the coefficient of North American regional factor with only 0.220. This coefficient indicates that the stock markets in the North America respond fastest to regional shocks.

The autocorrelation of country-specific factors varies across different markets. In 26 out of 34 markets, the coefficients of first-order autocorrelation of country-specific factors range from 0.1 to 0.3. The autocorrelations are either more than 0.3 or less than 0.1 in very few markets. The lowest autocorrelation is 0.065 for Spain, while the largest is 0.726 for Brazil. Among them, only the Brazil-specific factor is more persistent than world and regional factors, which indicates the longer impacts of country-specific factors on its own stock market.

The results show that most of the persistent comovements across markets in the world are captured by world factor. In only a few markets, such as Brazil and Chile, the higher-frequency comovements are captured by regional or country-specific factors.

2.4.4 Variance decompositions for different factors

For the purposes of this study, the analysis of variance decomposition is conducted to measure the relative contribution of the world, regional, and country idiosyncratic factors to the variance of stock market returns. In other words, its variance is decomposed into the fractions of the parts corresponding to world, regional, and country idiosyncratic factors. Since the two factors and idiosyncratic one are orthogonal, the variance of $y_{i,t}$ can be written as:

$$\mathrm{var}(R_{i,t}) = (b_i^{world})^2 \,\mathrm{var}(f_t^{world}) + (b_i^{region})^2 \,\mathrm{var}(f_{r,t}^{region}) + \mathrm{var}(\varepsilon_{i,t}) \tag{2.9}$$

Based on equation (2.9) above, the share of the variance of stock market returns attributable to these three factors can be estimated. Hence, it is possible to measure the roles relating to what extent the different factors impact the fluctuations of stock market returns. They are expressed as follows:

$$S_{f_i^{world}} = \frac{(b_i^{world})^2 \,\mathrm{var}(f_t^{world})}{\mathrm{var}(R_{i,t})};\; S_{f_{i,r}^{region}} = \frac{(b_i^{region})^2 \,\mathrm{var}(f_{r,t}^{region})}{\mathrm{var}(R_{i,t})};\; S_i = \frac{\mathrm{var}(\varepsilon_{i,t})}{\mathrm{var}(R_{i,t})}; \tag{2.10}$$

Where i=1,…, N; r=1,…, R; and $S_{f_i^{world}}$, $S_{f_{i,r}^{region}}$ and S_i are the shares of world, regional factors and country-specific component of the variance of stock market returns for country i, respectively.

Table 2.4.1 presents the variance shares of stock market returns contributable to each factor across 34 markets. Similarly, Table 2.4.2 presents the average variance shares for the markets within each region, as well as within the developed and emerging markets studied for this study.

<Tables 2.4.1 and 2.4.2 here>

Table 2.4 clearly indicates that world factor accounts for a large fraction of the variances of the stock market among most countries. More surprisingly, world factor explains more than 30 percent of the stock market variance in 29 out of 34 markets and more than 50 percent in 20 out of 34 markets. In particular, on average, world factor accounts for more than 65 percent of the variance in developed markets. In the context of economic globalization and financial integration, the results indicates that world factor plays an important role in driving the fluctuations of international stock markets, especially in developed markets. For example, world factor explains 84.23% of the stock market variance in Australia; 83.70% in the United States; 80.10% in the Netherlands; 79.55% in Canada; 75.83% in Norway; 74.18% in the United Kingdom; 71.40% in Austria; 69.24% in France; 67.78% in Ireland; 67.55% in Belgium; 65.57% in New Zealand; 66.18% in Denmark; 65.11% in Germany; 64.87% in Spain; 63.12% in Sweden; 61.93% in Switzerland; 60.13% in Hong Kong; 58.21% in Singapore; 55.00% in Italy; and 53.83% in Portugal. All these together suggest that the comovements of international stock market returns are mainly captured by world factor, especially in developed markets.

The regions with relatively apparent strong regional comovements of stock markets are Asia (developed), Asia (emerging), and South America. In these regions, regional factors attribute to relatively a bigger portion of the fluctuations of stock markets. For example, among six markets in Asia (emerging), regional factor accounts for an average of 27.08% of the stock market variances in the region. Surprisingly, in four out of six Asian markets, regional factors account for more than 25% of the variance, such as 42.36% in Thailand, 39.59% in Malaysia, 33.51% in Philippines, and 24.46% in Indonesia. In South America, regional factor also accounts for a significant fraction of the variance of stock markets, such as 32.88% in Argentina and 13.55% in Mexico. However, regional factors are of no real significant impact in the markets in North America and Europe, which is less than 5% of stock market return variance among 10 markets in these two regions. In particular, there is no crucial impact in the markets of Ireland and Norway, which are 1.74% and 0.76%, respectively. Yet, there are some exceptional markets in European region. For example, regional factor accounts for 22.61% and 22.54% of the variances in France and Germany markets.

On average, the idiosyncratic country-specific factor accounts for 32% of the variance of stock markets. Country-specific factors explain 1.44%, 33.01%, 40.72%, 26.30%, and 47.03% of the variances of the markets in Oceania, Asia (developed), Asia (emerging), Europe, North America, and South America. On the whole, in 14 out of 34 markets, country-specific factor accounts for more than 30 percent of the variances. Specifically in the following markets, country-specific factor accounts for more than 50 percent of its variation, such as 68.99% in Brazil; 64.14% in Taiwan; 57.52% in Chile; 57.30% in South Korea; 55.88% in Greece; 54.88% in Peru; and 50.71% in Japan.

<Figure 2.4 here>

From both Tables 2.4.1 and 2.4.2, there are also some important regularities:

Firstly, strong international stock market comovements exist since world factor accounts for a substantial portion of return variance in most markets. As shown in the histogram of Figure 2.4 of the return variance due to world factor, world factor explains a bigger portion of return variance in most markets. Specifically, world factor accounts for a significant fraction from 30% to 80% of return variance in more than 80% of the stock markets in my study.

As shown in Table 2.4.2, world factor plays a more important role in the shocks to developed markets than emerging markets. Here, world factor, on average, explains more than 65% of the stock market variances in developed markets. On the other hand, world factor explains approximately 32% in emerging markets. Among developed markets within different regions, world factor accounts for a much larger portion of return variances in Oceania at 75%, Asia (developed) at 56%, Europe at 64%, and North America at 82%. For emerging markets in South America and Asia (emerging), world factor accounts for 30% and 36% of the variances.

Next, regional factor plays a much more important role in the shocks of stock market returns for the markets in Asia (emerging) than other regions. On average, the Asian regional factor can explain 27% of the stock market variances in this region, which explains almost the same fraction of the impacts of world factor. Regional factors also account for a larger fraction of the stock market variances in Oceania, Asia (developed), and South America. Oppositely, the stock market variances are less attributable to region factor in North America and Europe. This suggests that a higher degree of comovements exists within regional stock markets, especially among emerging markets in Asia and South America.

Referring back to Table 2.4.1, it is evident that the roles of country-specific factors vary greatly across markets. In some markets, such as in Brazil and Taiwan, country-specific factors explain more than 60% of the variances. However, country-specific factors only account for 3.79% and 6.35% of the stock market variances in Hong Kong and Singapore. As shown in Table 2.4.2, it indicates that country-specific factors, on average, play a much larger role in accounting for the stock market variances in emerging markets than developed markets.

Lastly, both world and country-specific factors account for the main portion of the variances for most markets in this study. Together, the two factors account for more than 90% of the stock market variances in 17 out of 34 markets, especially in Europe and North America. This suggests that regional factors are less contributed to the fluctuations of stock markets in the two regions. The finding shows that there is no clear evidence of strong common regional factors that can be attributed to the fluctuations of European stock markets. This finding is in stark opposition to many studies that indicate the common European regional factors have been attributed to the stock market fluctuations in Europe. In contrast, world factor accounts for a substantial fraction of the stock market fluctuations in the region. That is, when the European markets display comovements, the main source is not distinctly from the European region, but rather worldwide. However, for the stock markets in such Asian (emerging) markets as Malaysia, the Philippines and Thailand, regional factor accounts for a large portion with more than 30% of the variances. This finding is consistent with those of several previous studies that examine the important role of regional impacts on stock markets because of their own characteristics of regional financial and economic integration in this region.

2.4.5 Robustness test

The robustness test of these results is considered with respect to examining the stock market real returns instead of nominal returns. This also extends the study for a different classification of region division. [9]

First of all, it is necessary to check whether the pattern of comovements of international stock markets would be altered if stock market real returns were employed instead of nominal returns in the above analysis. By using real returns rather than the aforementioned nominal returns, a very similar pattern of the comovements across international stock markets is uncovered. Furthermore, it is evident as that the factors that explain the fluctuations of stock markets have almost same role as above.

Secondly, a different way to sort the group of stock markets into different regions is utilized. Here, an alternative way to classify the stock markets for different regions has been followed. 10 Regarding the new classification of regions, the results indicate that the global factor plays almost the same role in driving the fluctuations of international stock markets. Moreover, under the different scenario of regional division, the results show that the regional factor also demonstrated a similar pattern.

In sum, although there may be some small quantitative differences between the estimates in this basic model and those in the various extensions previously discussed, the results of the patterns of international stock market comovements are very similar. All of the results show the important role of global factor in driving the fluctuations of international stock markets and the differences of stock market integration among developed and emerging markets.

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9 The results of these analyses are not reported here for saving space. The detailed results are available upon request.

10 Here I use another way to sort stock markets into different regions. Specially, among them, the regions of Oceania, Europe, and South America are same as original ones; Asian-Pacific developed region include stock markets of Canada, the United States, Japan, Hong Kong, and Singapore; and Asian emerging region include stock markets of Indonesia, Malaysia, Philippines, South Korea, Taiwan, and Thailand.

2.5 Do simple correlations mimic the measures of bilateral linkages on the basis of Bayesian dynamic factor analyses?

Correlation analysis has been widely used to measure the degree of bilateral stock market linkages. Thus, the objective in this section is to investigate simple pair-wise correlations among stock markets under this investigation. However, for both partially global as well as regional integrated financial markets, this study is particularly focused on the issue relating to what extent world and regional factors jointly impact the stock markets in the same region. Therefore, it is necessary to further investigate cross-country correlations of the stock markets within each region on the basis of the Bayesian dynamic factor model, as detailed above.

From section 2.4.4, the variance of $R_{i,t}$ for stock market in region *r* can be written as:

$$\mathrm{var}(R_{i,t}) = (b_i^{world})^2 \, \mathrm{var}(f_t^{world}) + (b_i^{region})^2 \, \mathrm{var}(f_{r,t}^{region}) + \mathrm{var}(\varepsilon_{i,t})$$

Hence, the covariance between markets *i* and *j* within the same region *r* can be derived as:

$$\mathrm{var}(R_{i,t}, R_{j,t}) = b_i^{world} b_j^{world} \, \mathrm{var}(f_t^{world}) + b_i^{region} b_j^{region} \, \mathrm{var}(f_{r,t}^{region}) \tag{2.11}$$

Therefore, the correlation between stock markets *i* and *j* within the same region *r* can be derived as the following:

$$\rho_{i,j} = \frac{b_i^{world} b_j^{world} \, \mathrm{var}(f_t^{world}) + b_i^{region} b_j^{region} \, \mathrm{var}(f_{r,t}^{region})}{\sqrt{\mathrm{var}(R_{i,t})}\sqrt{\mathrm{var}(R_{j,t})}} \tag{2.12}$$

Based on equation (2.12) derived from the Bayesian dynamic factor analysis above, it is possible to further measure the cross-country correlations within each region. Moreover, I investigate simple pair-wise correlations for the stock markets within the same region. Therefore, a reassessment can be made on whether simple correlation analysis mimics the measure of cross-market linkages on the basis of the Bayesian dynamic factor analysis in this study.

<Table 2.5 here>

Panel A and B in Table 2.5 present the results of the coefficients of both simple pair-wise correlation analysis and correlation analysis on the basis of the Bayesian dynamic factor analysis. On one hand, the results show that although simple pair-wise correlation analysis can partially measure the actual comovements of bilateral stock markets across the globe, it provides an imperfect and biased empirical depiction of actual market integration. For example, based on the correlation analysis from the Bayesian dynamic factor model, the bilateral stock market correlations of Australia-New Zealand, Canada-United States, Hong Kong-Singapore, and Hong Kong-Japan are highly integrated, while those bilateral correlations are not observed in the results of simple pair-wise correlation analysis. On the other hand, consistent with the findings based on variance decomposition in the Bayesian dynamic factor analysis, the results of simple correlation analysis provide evidence that developed markets are more highly correlated than emerging markets.

<Figure 2.5 here>

To better understand two different measures of bilateral correlations for different stock markets, Figure 2.5 plots the relationship between simple pair-wise correlation coefficients and the correlation coefficients estimated on the basis of equation (2.12) from the Bayesian dynamic factor model. As shown in Figure 2.5, the results indicate that simple pair-wise correlation analysis can partly measure the actual linkages among stock markets. However, in the presence of different modeling and some restrictions, there are some differences between these two correlation analyses. Simple correlation analysis cannot provide perfect depiction of their actual market linkages, especially for those higher or lower degrees of bilateral stock market correlations.

2.6 Can international stock market comovements be justified by real economic integrations?

In the previous sections, the results show that there are some differences of financial-market integration across developed and emerging markets. In a partially integrated global economy, the linkage between stock market comovements and the underlying economic integrations is of particular interest. International integration can fundamentally alter the nature of risks faced by investors and, therefore, stock market dynamics. In the literature, several researchers have investigated empirically the determinants of international stock market correlations (Ang and Bekaert, 2002; Dumas et al., 2003; Karolyi and Stulz, 1996, among others). Specifically, Dumas et al. (2003) employ the framework of an economic model to link the correlations of international stock markets to those of countries' outputs and investigated whether correlations of stock returns are justified by subsequent changes in national outputs. Carrieri et al. (2007) also show that financial linearization policies and financial market development play important roles in the integration of emerging markets. However, these examples in the literature are nonetheless vague as there are no comprehensive theories and empirical studies that specifically address this issue why the comovements of international stock markets vary across countries.

Therefore, it is important to determine how and to what extent international stock market comovements are associated with economic integration in the world. In this study, industrial production is employed as a proxy for output and for contemporaneous information of business cycles. As shown above, variance share of global factor can be used to measure global stock market integration across countries. This section also aims to employ the variance shares of global factor for industrial outputs to examine the degree of real economic integration of the underlying macroeconomic fundamentals across countries. Therefore, to explore the issue regarding how stock market integration can be justified by economic integration, it is possible to investigate the relationship between the variance shares of global factor for stock markets, as well as for industrial output.

<Figure 2.6 here>

Figure 2.6 presents the association between the degrees of international stock market comovements and those of countries' real economic integrations. The result shows that a higher degree of stock market comovement is closely accompanied by a higher degree of real economic integration, especially in developed economies. Based on the analyses in this study, stock markets also demonstrate higher degrees of comovements with international stock markets among more economically integrated and developed economies in the world. The global factor

accounts for substantial fractions of stock market volatility in the most integrated economies, such as 84.23% in Australia; 83.70% in the United States; 80.10% in Netherlands; 79.55% in Canada; 75.83% in Norway; 74.18% in the United Kingdom; 71.40% in Austria; 69.24% in France; 67.79% in Ireland; 70.89% in Belgium; 66.18% in Denmark; 65.11% in Germany; and 64.87% in Spain. Thus, these findings provide some support that economic integration provides a channel for financial integration. This partly explains the high degree of comovements of international stock markets documented in this study.

2.7 Conclusion

In this essay, I examine the common movements of stock market returns of a group of 34 countries across regions in the world. Specifically, I employ a Bayesian dynamic latent factor model to decompose stock market returns into world, regional, and idiosyncratic country-specific factors. I provide an in-depth analysis of the comovements of international stock markets across the world as well as within each region simultaneously. The main empirical findings are as follows.

Firstly, the results indicate that there is a significant world factor embodied in the fluctuations of stock market returns across markets in the world. Evidently, there exists a high degree of international stock market comovements. In particular, world factor accounts for a substantial fraction of the fluctuations of stock market returns in developed markets. The findings also indicate that the regional factor is another important source for the stock market fluctuations in South America and Asia, providing evidence of regional comovements of stock markets within the same region.

Secondly, the results indicate that the markets which co-move more with the worldwide markets are mainly developed markets, whose returns are less volatile. On the contrary, in emerging markets, regional factor and country-specific factor together account for more portion of the variance of stock market returns. In some particular emerging markets, such as Brazil, Korea, and Taiwan, among others, idiosyncratic country factor accounts for the bigger portion in explaining the fluctuations of these stock markets than the world and regional factors together.

The investigation of the property of factor persistence indicates that both the world factor and the Asian (emerging) regional factor have larger coefficients than other regional factors. This indicates the higher degrees of their persistence and the longer impacts of the past shocks. On the contrary, compared with higher degree of the persistence in the world factor, most country-specific factors with relatively smaller coefficients show their faster adjustments to their country-specific shocks. This demonstrates the longer impacts from world and regional shocks than from each country-specific shock.

Further, while investigating cross-country correlations of stock markets within each region, both simple pair-wise correlation analysis and the correlation analysis derived from the Bayesian dynamic factor model in this essay are applied to investigate bilateral stock market linkages within the same region. The result indicates that although simple pair-wise correlation analysis can partially measure actual bilateral stock market linkages within the same region, it provides an imperfect and biased empirical depiction of actual market integration. This finding is consistent with the finding in Pukthuanthong and Roll (2009). However, the results of simple correlation analysis provide evidence that developed markets are more highly correlated than emerging markets, which is consistent with the findings based on variance decomposition in the Bayesian dynamic factor analysis.

Lastly, when investigating the comovements of international stock markets, the analysis is extended to search for possible channel of the differences of international stock market comovements documented in this study. In a partially integrated global economy, the analysis indicates that the higher degree of a country's stock market comovement with international stock markets, the higher degree of its own real economic integration, especially in developed economies. The results suggest that real economic integration provides a channel for understanding international stock market comovements. These findings indicate that the degree of a market's comovement with international stock markets is closely related with that of its own country's economic integration in the world.

Chapter 3 Dynamic Correlation Analysis of the Realized Volatility Comovements in Asian Markets

3.1 Introduction

Cross-market linkages have been a prevalent phenomenon in modern financial theoretical and empirical research over recent decades. Accurate specification of stock market linkages is of very importance in financial decisions, such as portfolio allocation and risk management for risk-averse investors. For example, in a global integrated financial system, a shock in the Hong Kong market may make investors adjust their exposure to other international markets due to the possible information spillover of the Hong Kong market on other markets. One aspect of cross-market linkage researches usually examines the pattern of information flow across different markets. The interest of studying this aspect is motivated by the series of financial crisis in recent decades, such as East Asian “Asian flu” in 1997, “Russian virus” in 1998, Brazil crisis in 1999, and especially the recent global financial crisis over 2007-2009.

When we look at the fluctuations across different stock markets in the world, there always exist some strong movements in one market, which may correspond with the similarly strong movements in another one. If the definition of comovements can be based on the notion which describes a phenomenon of a market (or asset price) “moving with” other market (asset price, respectively), then we can conclude that the comovements can be defined as a pattern of positive correlation (Barberis et al., 2005). In other words, comovements can be defined with the correlation coefficient. The study of correlation is given as the comovements of stock markets with focusing on the markets in special region, such as Asian markets, or as the term “contagion” which is often considered as the “excessive” correlation among stock markets (Barberis, et al., 2005). Many studies use the term “correlation coefficient” to measure the comovements across stock markets (Boyer et al., 1999; Loretan et al., 2000; Forbes and Figobon, 2002; Corsetti et al., etc, 2005). Therefore, analysis of common movements among stock markets is an important and possibly effective way to better understand the functioning of regional financial system.

There are many studies in the literature on stock market comovements, market linkage, interdependence, and even spillovers of one market onto another, providing evidence of cross-market linkage. Although cross-markets linkage is a topic of ongoing interest to researchers and practitioners, it seems that we are still in the preliminary stage to fully understand cross-market linkage, and even far from being able to prevent the crisis transmitting across markets. The recent financial crises provide us with more opportunities to examine market correlation and information spillover across markets. This is particularly important when investigating financial crisis and their contagious effects, providing policy makers more sources to perfect the national and even the international financial system.

Previous studies on the stock market linkage and the financial contagion in financial crisis have not provided consistent results. In the earliest studies on international stock market linkages, Levy and Sarnat (1970) and Solnik (1974) examine short-term correlations of the returns across national markets and pointed out the existence of substantial possibilities to diversify internationally. Some recent studies (Hamao et al., 1990; Koch and Koch, 1991; and Longin and Solnik, 1995; etc) have exploited some more sophisticated econometric techniques to measure cross-market correlations, and find the evidence of significant linkages among stock markets in the world. Janakiramanan and Lamba (1998) empirically examine the correlation between the Pacific-Basin stock markets and they find that the US market influences all other markets, except for the relatively isolated market of Indonesia. Stock markets that are geographically and economically close and have a large number of cross-border listings tends to exert significant influence on one another, such as the stock markets in Asia.

Many previous studies have also shown the changes in stock market volatility over time (French et al, 1987; Schwert, 1989; Bekaert and Harvey, 1997; Corradi et al, 2009; etc). In particular, the degree of the dynamics of stock market volatility showed a great increase in the financial crisis. During the period of heighted volatility, stock markets are much more positively correlated (Kupiec, 1991; Forbes and Rigobon, 2002; etc). Several studies find that the increased volatility can increase the (extreme) degree of comovements, or there is increase in correlation coefficients conditional on the volatility of stock market when there is high degree of market comovements. Furthermore, in financial crisis, there often exists the phenomenon of volatility clustering[11], with periods of high and low (conditional or unconditional) variance. Mandelbrot (1963) notes the "volatility clustering" as follows: large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes. Especially when in financial crises, there often exists the phenomenon of volatility clustering. Kupiec (1991) shows there exists the phenomenon of the correlations in the stock market volatility and also finds that correlations among the volatilities of monthly stock market returns have increased over time. The results show that volatilities, particularly among the major markets, were more positively correlated in the second half of 1980s as compared with the first half of the decade.

Other studies on financial contagion also find significant increase in cross-market correlation of stock volatility in the Asia (Sachs et al, 1996). Ng (2000) finds that there exists volatility spillover effect from the Japan and the US markets to the Pacific-Basin markets. Similarly, some studies find volatility spillover effects among the stock markets in North and South America (Diebold, 2009). And Corradi et al. (2009) investigate conditional independence and find volatility transmission among international stock markets in their selected markets. When in the financial crisis, stock markets tend to move together with higher volatility, as large price change moves are interpreted as global news through the non-trading zones induced by costs of international transactions. During the period of heighted volatility, stock markets tend to be more positively correlated. All this raises the question whether the correlation of stock market volatility is higher during the financial crisis than before the crisis.

Motivated by previous studies, in this essay I want to investigate whether there are some common movements among Asian markets through the channel of the stock market volatility beyond what is implied by previous literature. Specifically, this essay aims to examine whether there is an increase in the comovements of stock market volatility among the main Asian markets after the crisis by employing correlation analyses of stock market linkages.

Unlike previous analyses focusing on the correlation of stock market price or market returns, this study aims to investigate the correlation of stock market comovements through

11 Time series of financial assets often exhibit the property of volatility clustering: large changes in prices tend to cluster together, resulting in persistence of the amplitudes of price changes. Volatility clustering often refers to the property if most heteroskedastic stochastic processes used in finance and economics.

higher moment of stock market volatility. Specifically, in this study I estimate time-invariant and time-varying correlation coefficients of stock market volatility in Asia and investigate whether there exists contagion effect among the Asian markets during the financial crisis. All this aims to further examine the regional stock market comovements through the channel of stock market volatility, and also to have a further and detailed investigation of financial contagion in Asia, thus helping us to understand the regional comovements during the financial crisis.

The remainder of the study is organized as follows. Section 3.2 describes the data and presents descriptive statistics. Section 3.3 presents the models employed in this study. Section 3.4 reports the empirical results. Section 3.5 investigates the transition of the realized volatility. And Section 3.6 contains the conclusions.

3.2 Data description and preliminary statistics

The data in this study are daily stock-price indices from the main Asian markets in the period of January 1st, 1995 to December 31st, 1999, [12] which consist of the closed observations of stock market prices expressed in local currency from Datastream International.[13] The indices of weekly realized volatility are estimated by using the daily stock market returns. Further, following the way by French, Schwert, and Stambaugh (1987) and Schwert (1989), I estimate the indices of weekly realized volatility, which are the sum of squared daily returns in each week as follows:

$$\begin{aligned} r_{i,t,j} &= 100*(\log p_{i,t,j} - \log p_{i,t,j-1}); \\ \sigma_{i,t}^2 &= \sum_{j=1}^{N_t} r_{i,t,j}{}^2 \end{aligned} \tag{3.1}$$

12 These markets were seriously affected by the 1997-1998 Asian financial crises.

13 Stock market index prices in this study are as follows: The Hang Seng Price Index for Hong Kong; the Korean Stock Exchange composite for Korea; the Kuala Lumpur Stock Exchange Composite Price Index for Malaysia; the Singapore Straits Times Price Index for Singapore; the Taiwan Stock Exchange weighted-price index for Taiwan; the Bangkok S.E.T. Price Index for Thailand; the Msdumaf Index for Malaysia; the Mseusinf Price Index for Indonesia; and the Nikkei 225 Price Index for Japan.

Where i is country i, t is week t in the period, and j is the trading day in week t; $p_{i,t,j}$ is the daily stock price index on date j in local currency; $r_{i,t,j}$ is daily stock returns; and N_t is the number of trading days in week t.

The reason to employ the weekly volatility in this study, instead of monthly ones, is to avoid the problem of non-synchronous trading and the day-of-the-week effects (see Dubois and Louvet, 1996; Ramchand and Susmel, 1998; Aggarwal et al., 1999; and Ng, 2000, among others). Moreover, the weekly realized volatility which is computed from the sum of the daily volatility in the week, largely overlap and thus information is shared among different markets.

<Table 3.1 here>

Furthermore, it aims to help investigate the dynamic relationship among stock markets during this special period. In particular, the different infected markets were impacted one after the other so frequently during the Asian crisis (see Table 3.1[14]), so it is necessary to examine how the Asian financial crisis affected the realized volatility of Asian markets one after another.

<Table 3.2 here>

Table 3.2 presents the summary statistics for the weekly realized volatility of the 9 Asian markets. Following the way in previous studies, I us the July 2nd, 1997 to split the sample period into two parts: Before crisis and after crisis.[15] As shown in Table 3.2, the mean of weekly realized volatility indices in the Asian markets is significantly higher after the crisis than before the crisis, even more than 10 times higher in both Malaysian and Indonesia.[16]

<Figure 3.1 here>

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14 Table 3.1 presents the date when stock markets were impacted during the 1997 Asian crisis.

15 On July 2nd, 1997, the Thailand Government gave up defending the value of its currency, the Baht, which triggered a significant depreciation of the currencies of Thailand and it neighboring Asian countries.

16 When the realized volatility in some markets is equal to zero, it means there were no trading days during the respective week for the market instead of the existence of no realized volatility.

Figure 3.1 plots the realized volatility indices in the whole sample period, which help to identify the difference of the indices and the similarity of the tendency among the Asian markets. As the figures show, there is a significant phenomenon of volatility clustering after Mid-1997. This phenomenon is consistent with other findings in the literature.

3.3 Empirical methodology

Correlation analysis is a widely used method to measure the relationship among different stock markets, especially for those within the same region. In this section, it builds on the previous findings of the market linkages by directly investigating the indices of the realized volatility of stock markets. Four different models are employed to investigate the correlations among the stock markets: two constant correlation models to investigate two different sub-periods, i.e., before crisis and post-crisis, and also two time-varying conditional correlation models.

3.3.1 Simple and adjusted simple correlation model

First, simple pair-wise correlation model is employed to investigate the relationship of the realized volatility among the different Asian markets. The simple correlation model is expressed as follows (see, Forbes and Rigobon, 2002):

$$\rho = corr(y_1, y_2) = \frac{\text{cov}(y_1, y_2)}{\sqrt{\text{var}(y_1)\,\text{var}(y_2)}} = [1 + \frac{\text{var}(\varepsilon_1)}{\beta_1^2\ \text{var}(y_2)}]^{-1/2} \tag{3.2}$$

where $y_{1,t}$ and $y_{2,t}$ refer to the realized volatility of stock markets 1 and 2, respectively, and $\varepsilon_{1,t}$ is a stochastic noise independent of $y_{2,t}$.

Through simple pair-wise correlation analysis, I examine whether correlation coefficients of the realized volatility among the different Asian markets showedan increase after the crisis. Here I also use the standard Z-test for statistics inference. To employ this statistics test, I first need to know and identify the source of crises beforehand. In this study, I follow the conventional way to consider the Thailand (with a breakpoint on July 2, 1997) and Hong Kong (with a breakpoint of October 17, 1997) to be Asian crises sources in this study. [17] [18]

The Z-statistics Test proposed by Morrrison (1983) is to test a null hypothesis of no increase in correlation, which is as follows:

$$T = \frac{Z_0 - Z_1}{\sqrt{[1/(N_0 - 3) + 1/(N_1 - 3)]}} \tag{3.3}$$

Where:

$Z_0 = 1/2 \ln[(1+\rho_0)/(1-\rho_0)]$;

$Z_1 = 1/2 \ln[(1+\rho_1)/(1-\rho_1)]$;

Z_0 and Z_1: The Fisher transformations of correlation coefficients before and after the crisis;
N_0 and N_1: The number of obersvatons before crises and after crises, respectively;
ρ_0 and ρ_1: The correlation before cirses and after crises, respectively.

This statistics are approximately normally distributed and are fairly robust to the non-normality of correlation coefficients, which are also adopted to examine the correlation coefficients in other studies (Basu, 2002; Corsetti et al., 2005; and Chiang et al., 2007; etc).

3.3.2 Dynamic conditional correlation model

Based on the statistical perspective, we expect the biased correlation coefficients because of the heteroskedasticity. To address the issue of heteroskedasticity, the Multivariate GARCH model proposed by Engle (2002) is employed to investigate the dynamic conditional correlation (DCC) in this study. The DCC-GARCH model, which accounts for heteroskedasticity directly, can help

17 Forbes and Rigobon (2002) argue that during the Asian crisis, the events in Asia became headlines news in the world only after Hong Kong market declined sharply in October 1997. Therefore, they use Hong Kong as the only source of Contagion and October 17, 1997 as the breakpoint of the whole sample period.

18 Another reason that Hong Kong is added in the analysis (Forbes and Rigobon, 2002) is that it is convenient for comparing my results with other studies in the literature with similar setting.

us to capture and investigate some of the evolutions in the conditional correlation structure. The general Multivariate GARCH(1,1) Model is expressed as follows:

$$\begin{aligned}
&y_t = \gamma_0 + \gamma_1 y_{t\text{-}1} + \varepsilon_t \\
&y_t = (y_{1,t}, y_{2,t}, ..., y_{n,t})^{'};\ \ \varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, ..., \varepsilon_{n,t})^{'}, \\
&h_{ii,t} = c_i + a_i h_{ii,t-1} + b_i \varepsilon^2_{i,t-1} \\
&\varepsilon_t \left| J_{t-1} \right. \sim N(0, H_t);
\end{aligned} \tag{3.4}$$

Where y_t: the vector of the realized volatility index at time t; and J_{t-1} is the information set up to time t-1.

And the conditional variance-covariance H_t can be specified and decomposed as follows:

$$\begin{aligned}
&H_t = D_t R_t D_t \\
&H_t = \begin{bmatrix} \sigma_1^2 & \sigma_{1,2} & ... & \sigma_{1,n} \\ \sigma_{1,2} & \sigma_2^2 & ... & \sigma_{2,n} \\ ... & ... & ... & ... \\ \sigma_{1,n} & \sigma_{2,n} & ... & \sigma_n^2 \end{bmatrix}
\end{aligned} \tag{3.5}$$

Where:

D_t: The (n $\times$ n) diagonal matrix of time-varying standard deviation from univariate GARCH models with on the i-th diagonal $\sqrt{h_{ii,t}}$, i = 1, 2, .., n

R_t: The (n $\times$ n) diagonal time-varying correlation matrix

The evolution of correlation in the DCC model can be expressed as follows:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u_{t-1}^{'} + \beta Q_{t-1}$$

$$R_T = (diag(Q_t))^{-1/2} . Q_t . (diag(Q_t))^{-1/2}$$

Q_t=($q_{ij,t}$): n $\times$ n time-varying covariance matrix of u_t

$\bar{Q}$=E[$u_{t-1} u_t^{'}$]: n $\times$ n unconditioal covariance matrix of u_t

$$\alpha + \beta < 1$$

$$where\ \ (diag(Q_t))^{-1/2} = diag(1/\sqrt{q_{11,t}}, ..., 1/\sqrt{q_{nn,t}})$$

The DCC model proposed by Engle (2002) involves two-stage estimation of the conditional covariance matrix H_t. In the first stage, univariate variance models are fitted for each of the realized volatility and estimates of $\sqrt{h_{ii,t}}$ are obtained; in the second stage, the residuals of market's realized volatility are transformed by their estimated standard deviations from the first stage. That is, $u_{i,t} = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$, where $u_{i,t}$ is then used to estimate the parameters of the conditional correlation.

Therefore, the correlation in the model can be written as follows:

$$\begin{aligned} \rho_{ij,t} &= \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}, \quad i, j = 1, 2, \ldots, n, \, and \;\; i \neq j \\ q_{i,j,t} &= \bar{\rho}_{i,j}\left(1-\alpha-\beta\right) + \alpha\left(\varepsilon_{i,t-1}\varepsilon_{j,t-1}\right) + \beta\left(q_{i,j,t-1}\right) \end{aligned} \tag{3.6}$$

This model captures not only the individual effects of volume and volatility, but also their interaction effects on any serial dependence in the residuals of OLS equations. Significant coefficient indicates which term adds information to the forecast of volume at time t and/or volatility. Thus, the GARCH formulation considers current variance, past variance and past error of the forecast of the variable in question (as well as information on the variance and the error of other variables and the covariability effects) to adjust the current forecast of the variable in question.

In this study, I only investigate the bivariate case, so the correlation coefficient under this condition can be written as follows:

$$\rho_{12,t} = \frac{(1-\alpha-\beta)\,\bar{q}_{12} + \alpha u_{1,t-1}u_{2,t-1} + \beta q_{12,t-1}}{\sqrt{[(1-\alpha-\beta)\,\bar{q}_{11} + \alpha u_{1,t-1}^2 + \beta q_{11,t-1}]}\sqrt{[(1-\alpha-\beta)\,\bar{q}_{22} + \alpha u_{2,t-1}^2 + \beta q_{22,t-1}]}} \tag{3.7}$$

As proposed by Engel (2002), the DCC model can be estimated through using the two-stage approach to maximize the log-likelihood function. Let θ denote the parameters in D_t , ϕ denote the parameters in R_t , and then the log-likelihood function is:

$$\begin{aligned} l_t(\theta,\phi) = {} & [-\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log\left|D_t\right| + \varepsilon_t{}' D_t^{-2}\varepsilon)] \\ & + [-\frac{1}{2}\sum_{t=1}^{T}(\log\left|R_t\right| + u_t{}' D_t^2 u_t - u_t{}' u_t)] \end{aligned} \tag{3.8}$$

This log-likelihood function can be maximized in the first stage over the parameters in D_t. Given the estimated parameters in the first stage, the correlation component of the likelihood function in the second stage can be maximized to estimate the correlation coefficients.

3.3.3 VAR Model

Beyond correlation analyses in the above models, Vector Auto-regressive analyses (VAR) are also employed to further investigate the correlation of the realized volatility in the Asian markets. VAR analysis which is often used to estimate a dynamic simultaneous equation system helps understand the transmission of uncertainty of the realized volatility across markets.

3.3.3.1 Time-invariant VAR Model

In this section, time-invariant VAR Model is employed to investigate simple correlation among the main Asian markets. The time-invariant VAR model with p-order is written as follows:

$$y_t = B_0 + \sum_{k=1}^{p} B_k y_{t-k} + u_t \qquad (3.9)$$

Where y_t is a vector of the realized volatility of the stock markets; B_i is the constant coefficient matrices, p is the number of lags, and $u_t = (u_{1t}, u_{2t}, \ldots, u_{nt})'$ is an unobservable i.i.d. zero mean error term with time-invariant variance-covariance Ω.

Here, lag length in the VAR model is chosen by the AIC criterion, Schwar'z criterion, and likelihood ratio test. In this study, the tests suggest that 1-lag is the optimal length for most stock markets. I split the sample period into two sub-periods. And the model is estimated by using OLS. Here the vector of innovation is assumed to be $\mathrm{var}(u_t) = \Omega$. Therefore, the conditional variance-covariance matrix can be estimated as $\hat{\Omega}$. In bivariate VAR(p) model, the conditional variance-covariance is written as follows:

$$\hat{\Omega} = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix} \qquad (3.10)$$

By employing the formula of correlation coefficients, the conditional correlation coefficients between y_{1t} and y_{2t} can be written as follows:

$$\rho_{12} = \frac{\sigma_{12}}{\sigma_1 . \sigma_2} \tag{3.11}$$

3.3.3.2 Time-Varying VAR model

Further, time-varying VAR Model is also employed to investigate the relation of stock markets, which are expressed as follows: The model in this section is a multivariate time series VAR model with incorporating time-varying coefficients and time-varying variance-covariance matrix of the addition innovations. The main objective allowing for time variation both for coefficients and variance-covariance matrix is to capture the possible nonlinearities and time variation in the underlying market structure change of the model.

As in the time-invariant VAR Model above, the VAR lag length is chosen by the AIC criterion and Schwarz's criterion, which suggests that 1-lag is the optional length for most Asian stock markets. Therefore, for simplicity, here I assume the Time-Varying VAR(p) (TV-VAR) model with the 1--lag as follows:

$$y_t = B_0 + B_{1t} y_{t\text{-}1} + u_t \tag{3.12}$$

Where B_{1t} is the time-invariant coefficients matrix; u_t are heteroscedastic shocks with time-varying variance-covariance matrix Ω_t. Without loss of generality, consider the triangular reduction of Ω_t, defined by

$$\Omega_t = A_t^{-1} H_t (A_t^{'})^{-1} \tag{3.13}$$

Where A_t is the lower triangular. Here the vector y_t includes two variables $y_t = \begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix}$, so the matrix A_t can be written as follows:

$$A_t = \begin{bmatrix} 1 & 0 \\ a_t & 1 \end{bmatrix} \tag{3.14}$$

And similarly, the diagonal matrix of H_t can be written as follows:

$$H_t = \begin{bmatrix} h_{11,t} & 0 \\ 0 & h_{22,t} \end{bmatrix} \tag{3.15}$$

Then (3.12) can be rewritten as

$$y_t = B_0 + B_{1t} y_{t\text{-}1} + A_t^{-1} H_t^{1/2} \varepsilon_t, \quad \varepsilon_t \sim N(0, I_n). \tag{3.16}$$

Let $h_t = (h_{1t}, h_{2t})$ with $h_{jt} = \log h_{jj,t}^{1/2}$, for j=1, 2,and t=S+1,…,n. As suggested by Primiceri (2005), the parameters in the time-varying VAR(1) Model are assumed to follow a random walk process:

$$\left.\begin{aligned} B_{1,t+1} &= B_{1t} + u_{bt} \\ a_{t+1} &= a_t + u_{at} \\ h_{t+1} &= h_t + u_{ht} \end{aligned}\right\}, \quad \begin{pmatrix} \varepsilon_t \\ u_{bt} \\ u_{at} \\ u_{ht} \end{pmatrix} \sim N\left(0 \quad , \begin{bmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_b & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{bmatrix} \right) \tag{3.17}$$

For t=s+1,…,n, where $B_{s+1} \sim N(\mu_{B0}, \Sigma_{B0})$), $a_{s+1} \sim N(\mu_{a0}, \Sigma_{a0})$ and $h_{s+1} \sim N(\mu_{h0}, \Sigma_{h0})$. This assumption of random walk presents the advantages of focusing on permanent shifts and reducing the number of parameters in the estimation procedure since the sample period is just a finite period of time and not forever. The shocks to the innovations of the time-varying parameters are assumed uncorrelated among the parameters $B_t,\ a_t,\ and\ h_t$. I further assume that $\Sigma_B,\ \Sigma_a,\ and\ \Sigma_h$ are all diagonal matrices. The drifting coefficients and parameters are modeled to fully capture possible changes of the VAR structure over time. The dynamic specification is adequate to permit the parameters to vary even if the shocks in the processes driving the time-varying parameters are uncorrelated.

In the time-varying VAR Model which includes a great number of parameters, I employ the MCMC method to estimate them. In Bayesian procedure, it allows to estimate more general specifications for a non-trivial number of equations.[19] The Bayesian approach allows us to produce the sample drawn from a posterior distribution of parameters including the unobserved latent variables (see Chibs, 2001). Therefore, when using time-varying parameters in the model as latent variables, the model can be formed as a state-space specification.

The important step to construct an efficient sampling scheme for the time-varying VAR model is the joint sampling of $B = \{B_t\}_{t=s+1}^{n}$ (and in turn, $a = \{a_t\}_{t=s+1}^{n}$, $h = \{h_t\}_{t=s+1}^{n}$) conditioned on the rest of the parameters, which is better than the approaches that rely on one-at-a-time sampling. To accomplish this strategy, the simulation smoother (de Jong and Shephard, 1995; Durbin and Koopman, 2002) is suitable for sampling the time-varying coefficient B and parameter a because the model can be written in a linear Gaussian state space form.

The model has the forms with a non-linear non-Gaussian state space. Therefore, I need to find some ways of sampling. Here I follow the conventional method of mixture sampler that's been widely used in the financial and macroeconomics literature (Kim et al., 1998; Primiceri, 2005; and Omori et al., 2007, among others). The details of the procedures can be found in Appendix A.

Followed the technical methods and procedures above and those in the Appendix A, I can have the estimation of both the time-varying parameters and variance-covariance matrix Ω_t in the VAR Model. In particular, for the time-varying bivariate VAR(1) model, the estimation of time-varying conditional variance-covariance matrix can be written as follows:

$$\Omega_t = \begin{bmatrix} \sigma_{1,t}^2 & \sigma_{12,t} \\ \sigma_{12,t} & \sigma_{2.t}^2 \end{bmatrix} \tag{3.18}$$

Thus, time-varying correlation coefficient between y_{1t} and y_{2t} at time t is as follows:

$$\rho_{12} = \frac{\sigma_{12,t}}{\sigma_{1,t}.\sigma_{2,t}} \tag{3.19}$$

19 For specification and estimation of a time-varying VAR model, see Primiceri (2005). And for specification and estimation of a time-varying SUR model, see Chib and Greenberg (1995).

Investigating time-invariant and time-varying correlation coefficient on the basis of the VAR models, it can help us to better understand how the realized volatility comovements among the main Asian markets have been evolved before the crisis and after the crisis.

3.4 Empirical results

3.4.1 Simple pair-wise correlation analysis

<Table 3.3 here>

First, I simply choose the July 2nd, 1997 as the breakpoint mentioned above. The results of the simple pair-wise correlation coefficients between the realized volatility of different markets during the two periods are reported in Table 3.3.1. The results show that the null hypothesis of no correlation increase is rejected by 28 out 36 coefficients. Among the remaining 8 coefficients, half of them are with Malaysia market due to the capital control in this country in 1998.

Secondly, some questions are raised whether the source country of financial crisis matters. Thus, if I change the crises source of country, I use the country as the crises source according to the order of date when the infected markets were impacted during the crises.[20] The whole sample period is divided into two periods based on the date of the order, and then the new simple pair-wise correlation coefficients are estimated for the Asian markets. As shown in Table 3.3.2, the result shows that the null hypothesis of no correlation increase is rejected by 29 out 36 coefficients. It is similar to what is presented in the above section. By using Z-test, I only find that the null hypothesis is rejected at the 10% level in 25 out of 36 cases after adjusting the infected markets according to the impacted date.

3.4.2 Dynamic conditional correlation analysis using GARCH Model

As simple-correlation analysis highlights the realized volatility in the different periods with a given window, I further discuss this issue by investigating the time-varying characteristics of

20 The dates the infected markets were impacted during the crisis can be found in Table 3.3.1 in the Appendix.

correlation matrix in those markets. To simplify the presentation, as suggested in the literature, here only the Thailand and Hong Kong markets are chosen as the crises sources in this study. I study the dynamic patterns of correlation changes by focusing on the Thailand market with other 8 Asian ones and then the Hong Kong market with other 8 Asian ones. I aim to compare the dynamic different pair-wise correlation coefficients in two different phases and then investigate the dynamic of the realized volatility comovements in the Asian markets.

<Figures 3.2 here>

Figure 3.2.1 present the pair-wise dynamic conditional correlation coefficients (and mean values of the coefficients in two different periods) between the realized volatility of Thailand and those of Indonesia, Malaysia, Philippines, Singapore, Taiwan, Hong Kong, South Korea, and Japan during the period, respectively.[21] It is of interest to compare the dynamic correlation coefficients and the mean values together. In the figure, the blue line shows the time-varying correlation derived from the DCC-GARCH model in the sample period. And the green line shows the breakpoint and the mean values in the two different periods by using the breakpoint.

Broadly speaking, the dynamic conditional correlations are higher in the sub-period of mid 1997 to the later 1999, when the most of Asian stock markets were experiencing a downturn except the correlation between Thailand and Philippine. In contrast, during the sub-period before crisis from 1995 to mid 1997, the conditional correlations are below the average. All this shows that the dynamic correlation coefficients are significantly increased when the Hong Kong market was experiencing the downturn in Oct. 17th, 1997.

Figure 3.2.2 present the pair-wise dynamic conditional correlation coefficients of the realized volatility (also mean values of the coefficients in two periods) between the Hong Kong market and each of the markets during the period, including Thailand, Indonesia, Malaysia, Philippines, Singapore, Taiwan, South Korea, and Japan. The result is similar to the Thailand's case. The dynamic correlations between the Hong Kong market and 8 other Asian markets are

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21 Here I also just choose the July 2nd, 1997 as the breakpoint to defining the two periods of before-crisis and after-crisis, which is the same as I did in the simple pair-wise correlation model. And then I calculate the mean of the dynamic correlation coefficients in two different periods.

higher in the second period than the first period, except the one between Hong Kong and Malaysia. The possible reason is due to the Malaysia's capital control in 1998.[22] The isolation of Malaysian markets could be explained by its unique response to the regional crisis. During the crisis, Malaysia significantly increased market regulation and severely restrict capital control, which may isolate the market from other markets in Asia.

And there is also a clear phenomenon of continuously upward tendency in the correlation between the Hong Kong market and other Asian markets of Philippine, Taiwan, South Korea, and Japan, respectively. These increasingly larger correlation coefficients indicate that these national markets were becoming more closely integrated with the Hong Kong market, which is commensurate with the increasing importance of intra-Asian business in the 1990s. In particular, for the realized volatility in the Taiwan and South Korea markets, there is a sudden jump in the correlation coefficients among the Hong Kong and those two markets. The period of sudden jump of the correlation coefficients coincide with the time when the Hong Kong market was experiencing the crash in Oct, 1997. Even though there is a decrease in the correlation coefficients, on average, between the Hong Kong market and Singapore market in the two periods, it also experiences a significant upward shift in the correlation during the periods when the two markets collapsed one after another in the Mid-1997 period in Figure 3.2.2.

<Table 3.5 here>

To illustrate a clearer picture of the difference of the dynamic correlation in the two periods with pre-crisis and post-crisis, the averages of those correlation coefficients for the two periods are also reported in Table 3.5. From Panel A in the table, clearly, there is an increase in the degree of the correlation between the Thailand and other Asian stock markets after the crisis, respectively. And, similarly, from Panel B, there is also a significant increase in the degree of the correlation between the Hong Kong and other Asian markets after the crisis, except the one between the Hong Kong market and Singapore market. In particular, for the correlations between Hong Kong Thailand, Hong Kong and Philippine, Hong Kong and Taiwan, Hong Kong and

22 Chiang, et al. (2007) also found there was a decrease in the correlation after the crisis between the Malaysia stock market returns and those of Hong Kong market. In, et al. (2002) also found that Malaysian market shows a quite different pattern from other Asian markets.

South Korea, and Hong Kong and Japan, the averages of the correlation coefficients were increased from 0.4989, 0.3315, 0.3902, 0.3624, and 0.3412 before crisis, respectively, to 0.5726, 0.4622, 0.5969, 0.5737, and 0.5737 after crisis, respectively. The results show that those stock markets are much more integrated with the Hong Kong market during the period of post-crisis.

3.4.3 Constant correlation analysis using time-invariant VAR Model

In this part, I follow the same way as in the simple correlation model above to choose the July 2nd, 1997 as the breakpoint to divide the sample period into before crisis and after crisis. The results of pair-wise correlation coefficients between the realized volatility of the Asian markets in the two periods are reported in Table 3.4.

<Table 3.4 here>

The results show that the null hypothesis of no increase of the correlation is rejected by 26 out of 36 coefficients. These results based on in the time-invariant VAR(p) analysis are similar to those in the pair-wise correlation analysis. The markets' correlation can't reject the null hypothesis, including as follows: PH-MA, PH-JP, MA-IN, MA-SG, MA-HK, MA-SK, SG-HK, SG-SK, SG-JP, and SK-JP, respectively. Interestingly, the results show that among the 10 pair-wise correlation coefficients, 8 out of them except MA-SK and SG-SK are exactly the same as the results based on in the pair-wise correlation analysis.

3.4.4 Dynamic correlation analysis using time-varying VAR Model

In order to investigate the dynamic correlations using the time-varying VAR model, I follow the techniques described in section 3.3.3 and Appendix and then need to choose the prior for the parameters for the procedure. As to the choosing of the prior, I follow the general way suggested by Primiceri (2005) to run the first 10 observation in the subsample to draw the prior distribution of the initial state in the process of the time-varying parameters. And the following priors are assumed for i-th diagonal of the covariance matrices:

$$(\Sigma_B)_i^{-2} \sim Gamma(10, 0.01); \quad (\Sigma_h)_i^{-2} \sim Gamma(2, 0.01);$$

For example, the mean and the variance of B are chosen to be the OLS point estimates and four times its variance in a time invariant VAR, estimated on the small initial subsample. In the same way, I can obtain other reasonable prior for other parameters. Taken together, the initial state of the time-varying parameters can be expressed as follows:

$$\mu_{B_{1,0}} = B_1;\ \mu_{h_0} = \log\sigma_0^2;\ \text{and}\ \Sigma_{h_0} = \Sigma_{B_{1,0}} = 4\times I$$

After the prior parameters are set up, then I apply the techniques and prior parameters to estimate the model. The Gibbs sampler is iterated 5,000 times, of which the first 2,000 is discarded as burning-in replication for the convergence. The empirical results are reported in Figure 3.3.

<Figures 3.3 here>

Figure 3.3.1 presents the time-varying conditional correlation of the realized volatility among the Thailand market and other Asian markets during the whole sample period and the mean values of the coefficients in two different periods (given by the green line) in time-varying VAR model. As expected, the results on the tendency of correlation coefficients are very similar as those I have from the GARCH model above. As shown in Figure 3.3.1, most of the dynamic conditional correlation showed an increase after the crisis, including the following correlation coefficients: TH-PH, TH-IN, TH-SG, TH-TW, TH-HK, TH-SK, and TH-JP. The only exception is the correlation between Thailand market and Malaysia market, which generally showed a clear decrease after the crisis.

Similarly, Figure 3.3.2 presents the time-varying conditional correlation of the realized volatility among the Hong Kong market and other Asian markets during the whole sample period and the mean values of the coefficients in two different periods (given by the green line) in time-varying VAR model. Similarly, the dynamic conditional correlations of Hong Kong and other markets, including Thailand, Philippines, Singapore, Taiwan, South Korea, and Japan, clearly showed an upward shift in the period of post-crisis. In particular, the conditional correlations showed a sudden jump during the period when Hong Kong market showed the great downturn in Oct. 1997. And, interestingly, the feature that the conditional correlation between the Hong Kong market and the Malaysia market is generally decreased after the crisis is the same as that of between Thailand and Malaysia shown in Figure 3.3.1.

<Table 3.6 here>

As in GARCH analysis above, here the mean values of the dynamic correlation coefficients when using time-varying VAR model during the two different periods are reported in Table 3.6. From Panel A in Table 3.6, it shows there is a significant increase in the degree of the correlation between the Thailand market and other Asian markets after the crisis, except the one between Thailand market and Malaysia market. Similarly, And, Panel B in Table 3.6 also shows there is an obvious increase in the degree of the correlation between the Hong Kong market and other Asian markets after the crisis, except the one between Hong Kong market and Malaysia market.

Taken all together, the results show that the correlation, whether the constant correlation or the dynamic conditional correlation among most Asian markets, generally showed an increase after the crisis. In another words, there exist much more significant and stronger comovements of the stock market volatility for most markets in this region after the crisis.

3.5 Transmission of stock market volatility

Based on the VAR analyses above, the stock market volatility in the Asian markets has stronger impact to one another, especially after the crisis. Therefore, I further investigate how the fluctuation of the stock market volatility in one market affects other Asian markets and thus help understand the transmission of uncertainty from the volatility in the two periods, which can be achieved by impulse response analysis and variance decomposition analysis.

The impulse response analysis can be used to investigate the effects of a shock to one endogenous variable to other variables in the VAR system. It also can trace the speed and the persistence of the shocks and then enables the examination of time structure of the transmission. Furthermore, the analysis of variance decomposition is used to investigate the importance of the innovation of other variables in the system, which reveals to what extent the innovation of the variable can be explained by the shock from other different variables.

<Figures 3.4 and 3.5 here>

Figures 3.4 and 3.5 plot the results of impulse response analysis and Monte Carlo simulated 95% confidence in dashed red line. Figure 3.4 plots the impulse response functions of different Asian markets response to a one S.D. innovation of the Thailand market before crisis and after crisis, respectively. And Figure 3.5 plots the impulse response functions of different Asian markets response to a one S.D. innovation of the Hong Kong market before and after crisis, respectively.

A few results stand out. First, the responses of different Asian markets to the innovation of the Hong Kong market are generally much stronger than to the Thailand market. This finding reflects that the Hong Kong market has a strong impact on other Asian stock markets than the Thailand market. Secondly, the responses of realized volatility of other Asian markets to both Hong Kong and Thailand markets are much stronger after the crisis than before crises. This finding indicates the comovements of the Asian markets are stronger after the crisis. In particular, the responses of Malaysia, Indonesia, and Singapore to Hong Kong and Thailand markets were greatly increased after the crisis. Finally, the response of other Asian stock markets to Thailand and Hong Kong greatly decreased over the time, and the innovation of realized volatility from these two markets has a very small influence on other Asian markets after 3 periods (3 weeks).

<Table 3.7 here>

The results of the variance decomposition analysis for each period are reported in Table 3.7.[23] Similarly, the analysis of variance decomposition is also divided into two periods as before. In decomposition analysis, I examine the degree of Thailand contribution and Hong Kong contribution to the innovation of other Asian markets and also to investigate whether the sock market volatility linkage among the Asian markets consolidated during the financial crisis.

23 For saving the space, here I just report the decomposition of variances for the 1st, 5th and 10th Period.

From Table 3.7, it shows that the variance of each Asian stock market is mainly due to its own variance instead of from the Hong Kong market or the Thailand market. The patter was as expected. An interesting feature of the decomposition of the Asian markets is that the domestic contribution of its own variation substantially decreases in the period after the crisis. In another words, there is a significant upward shift on the portion of contribution from both the Thailand and Hong Kong markets after the crisis, compared with those before the crisis.

Based on the impulse response analysis and variance decomposition analysis, I find the strong information transmission structure across the Asian markets by using the realized volatility index during the two periods. And such linkage structure is much stronger during the financial crisis.

3.6 Conclusion

This study investigates the comovements among the main Asian stock markets by the channel of studying the correlation of the realized volatility among these markets during the 1997 Asian financial crisis. I first estimated the simple pair-wise correlation between the Asian stock markets and then applied the DCC-GARCH model of Engel (2002) to estimate the time-varying conditional correlation. Furthermore, I employ both time-invariant VAR(p) model and time-varying VAR(p) model to investigate the time-invariant and time-varying conditional correlation of the realized volatility among those markets, respectively.

Taken all of those results together, it shows that there is a significant increase of correlation coefficients after the crisis for most of the Asian stock markets. Although the markets dynamic correlations show some fluctuation, it provides a detailed description of the strong comovements of the realized volatility among the Asian stock markets. These correlations are significantly higher after the crisis, suggesting there are higher comovements between most of the Asian stock markets. In particular, the dynamic conditional correlations of Hong Kong and most of other Asian stock markets showed a sudden jump during the period when Hong Kong market experienced the great downturn in October, 1997.

Overall, from the impulse response analysis and variance decomposition analysis, I can conclude that the Hong Kong market has a stronger impact on other Asian stock markets through the realized volatility than the Thailand market. The response of other Asian stock markets to the innovation of the Hong Kong and Thailand markets were greatly increased after the crisis. And in the variance decomposition analysis, I can also find that the contribution to the variance of other Asian markets from the Hong Kong market and Thailand market showed an increase after the crisis.

And one more interesting feature of the correlations is the relationship between Malaysia market and other Asian stock markets. It shows the isolationist responses of the Malaysian authorities to the crisis appear to have contributed to a lessening in Malaysia's linkage within other Asian stock markets.

Chapter 4 On International Stock Market Comovement and Macroeconomic Fundamentals

4.1 Introduction

Globalization has accelerated in the past two decade. There are rapid increases in both cross-country financial flows and international trade in goods and services. Nowadays almost every single country's macroeconomic performance and financial market are no longer immune to the development in other parts of the world. These increased financial and trade linkages across countries have stimulated a large literature on international business cycle comovements such as Kose et al. (2008) as well as on measuring financial market integration such as Pukthuanthong and Roll (2009) and Carrieri et al. (2007) among many others.

In this chapter, I study jointly the comovements of stock market prices as well as other major macroeconomic variables from a large group of countries. I am particularly interested in the link between stock market movements and the underlying macroeconomic fundamentals in a perhaps partially integrated global economy. International integration can fundamentally alter the nature of risks faced by investors and, therefore, stock market dynamics. For example, in an isolated economy, the market risk of that country is a priced systematic risk. In a perfectly integrated world economy, however, only the exposure to the global stock market risk will be priced. Similarly, the underlying macroeconomic risks that drive much of the stock market movements will also be different. In an isolated economy, the macroeconomic fluctuations of that country are perhaps the most important driving force of its stock market movement. In an integrated world economy, an individual country's stock market will probably respond more to the world business cycle shocks than to its own macroeconomic fluctuations. Indeed, using a dynamic factor model estimated on monthly data on a group of 34 countries from 1995 to 2009 via Bayesian methods, I find that the global factors account for a significant portion of an individual country's stock market volatility as well as its macroeconomic fluctuations. The global macroeconomic shocks have strong effects on the price movement of the global stock market as well as that of an individual market, and a country's exposure to the global stock market risk can be largely explained by that country's exposure to the global macroeconomic risks.

This essay is related to the two strands of literatures. One strand is the empirical study of international stock market integration. In the literature, there are a wide variety of studies of market integration through measure of markets' correlation or common factor (Forbes and Figobon, 2002; Hamao et al, 1990; Brooks and Del Negro, 2005; among others). Instead of focusing only on markets, some recent studies have further explored the market integration through correlation analysis by incorporating part of macroeconomic fundamentals. For example, Dumas et al. (2003) propose a framework that contains a model for output and an intertemporal financial model for the stock market. Their results indicate that under the hypothesis of integrated financial markets, the international stock market correlations can be matched to the levels of actual stock market linkages. Carrieri et al. (2007) employ GARCH model to investigate the evolution of market integration in eight emerging countries. They find that the correlations of national index returns with the world are significantly lower than estimated integration indices on the basis of real activity.[24]

My focus on market integration differentiates my work from other previous studies that only examine the market's correlation or common factor. Pukthuanthong and Roll (2009) illustrate that as in previous studies, the correlation analysis of measuring the broad cross-markets integration poorly mimics other measures of integration. They further discover that there has been increased market integration for most countries over the years, but this cannot be indicated by the simple correlation analysis. Thus, they derive a new integration measure based on the explanatory power of a multi-factor model to investigate the global integration.[25] Similarly, Bekaert et al. (2009) employ risk-based factor models to investigate country-industry and country-style portfolios. Their results provide the evidence of international stock return comovements and also show that the factor model can better capture the covariance structure

24 A similar study by Chambet and Gibson (2008) utilized the GARCH-M model to investigate the relationship between the level of financial integration in emerging markets and the indicator of country's trade openness and concentration. They find that countries with an undiversified trade structure have more integrated financial markets.

25 Similar studies of market integration that employ the factor model have also been conducted by Eiling and Gerard (2007) and Brooks and Del Negro (2005).

more successfully than the previous popular Heston-Rouwenhorst model (Heston-Rouwenhorst, 1994). However, these studies of common factor usually only focus on markets without incorporating the underlying macroeconomic fundamentals. In particular, the macroeconomic variables will especially important as they will most likely have strong effects on the price movement of stock markets and thus, may also affect the evolution of their financial market integration. Therefore, I argue that it is more conceivable and subsequently imperative to incorporate the underlying macroeconomic fundamentals when investigating market integration.

This essay is also related to the recent literature on the comovements of international business cycles. Over the recent decades, there are a wide variety of studies of the macroeconomic activity comovements via investigation of the common factor. In recent prominent examples, including Kose et al. (2003, 2008), Canova et al. (2007), Crucini et al. (2008), and Artis and Okubo (2009), among others, dynamic factor model is used to investigate the common shocks to macroeconomic fundamentals across countries. In this vein, because global factor is an important tool to investigate the common macroeconomic shocks across counties and because it can be also employed to measure the underlying global macroeconomic risks for the global stock market, it is therefore necessary for us to briefly review the studies in the literature of global factor of macroeconomic fundamentals.

The existing research on global macroeconomic developments is primarily focused on the common movements of industrial output and productivity across various countries.[26] Gregory et al. (1997) employ a dynamic factor model to identify the common factor of macroeconomic aggregates fluctuations in G7 countries.[27] Moreover, research conducted by Stockman (1988) and Norrbin and Schlagenhauf (1996) find that a substantial fraction of the variation in industrial production is due to global and country-specific components in main industrialized economies.

26 For additional details on the summary of recent evidence on the evolution of dynamic international business cycles, see Stock and Watson (2005).

27 Doyle and Faust (2005), Kose et al. (2005) and Stock and Waston (2003, 2005), also investigated the fluctuation among G7 economies. Each of these studies found an increased importance of common shocks as a driving force of output fluctuation across countries.

Furthermore, it should be noted that the inflation fluctuations across countries are similar to the regularities of real business activity. Numerous recent studies focusing on the investigation of global inflation movements provide the evidence of the so-called “worldwide great inflation.” For example, Ciccarelli and Mojon (2010) use a dynamic factor model to measure the inflations and subsequently found that the inflations in industrialized countries are largely a global phenomenon. Their results showed that the common factor accounts for a significant fraction of the variances in 22 OECD countries, which are similar to the results of Neely and Rapach (2009).[28]

Finally, some studies have explored global monetary markets and have further investigated to what extent monetary policies across countries move together (Henriksen et al., 2009). One of the main purposes of this study is to examine whether these changes, such as monetary integration in Europe, have impacted monetary policies across countries. A variety of channels may potentially affect monetary policies across countries. For example, in the European Economic and Monetary Union, the member countries will most likely influence each other to adopt similar monetary policies. The global macroeconomic shocks may also potentially influence the common movement of monetary policies. All these factors could impact the central banks in their response to common shocks, and thus result in the comovements of their monetary policies (Henriksen et al., 2009). In summary, a variety of macroeconomic shocks, as well as the economic and political pressures for central banks to respond similarly to the shocks, is capable of driving the comovements of monetary policies across countries.

Therefore, it can be argued that these global factors can be used to measure the common macroeconomic fundamental shocks in the world. Furthermore, these global factors can also be employed to characterize common global macroeconomic risks. For example, global factor, which measures the common shock to industrial productivity across countries in the world, can be utilized as a proxy for global macroeconomic risk from economic activity.

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28 Neely and Rapach (2009) employ the Bayesian dynamic factor model to investigate the international comovments in inflation rates for a larger sample, which include industrialized and emerging countries. The findings of other studies on the dynamic factor on global inflation (Hakkio, 2009; Mumtaz and Surico, 2008) are similar to the findings that comovements of global inflation exist across countries (Ciccarelli and Mojon, 2002)

The rest of this essay is organized as follows. Section 4.2 describes the empirical methodology. Section 4.3 summarizes the data used in the study. Section 4.4 presents major empirical results. Section 4.5 reports the robustness test. Section 4.6 summarizes the main findings and concludes the study.

4.2 Empirical methodology

4.2.1 Bayesian dynamic factor model

In order to tackle the issues discussed above, I employ Bayesian dynamic latent factor models to decompose stock market returns and other major macroeconomic variables into common global factors and idiosyncratic country-specific factors. In this study, the dynamic unobserved global factor is designed to characterize the common movements across economies in the world.

Let N denote the number of countries, and T the length of the time series. The observable variables of different countries are denoted $y_{i,t}$, for i =1, …,N, t=1,…,T. There is only one type of dynamic factor I want to identify in this study, i.e. the global factor (f_t). Thus for country i, the specification of dynamic latent factor model can be written as follows:

$$y_{i,t} = \lambda_i f_t + \varepsilon_{i,t} \tag{4.1}$$

Here $y_{i,t}$ represents the observables in month t at country i; f_t represents the global factor for all countries, to which each country respond differently through λ_i, and $\varepsilon_{i,t}$ represents the country-specific idiosyncratic shock to the variables in country i, all in month t.

The evolution of global factor is assumed to be governed by an autoregression of p-order with normal errors.

$$f_t = \phi_1 f_{t-1} + \phi_2 f_{t-2} + ... + \phi_p f_{t-p} + u_t \tag{4.2}$$

Where $Eu_t u_t = \sigma_f^2;$ and $Eu_t u_{t-s} = 0;$ for all s≠0.

Similarly, the country-specific idiosyncratic terms $\varepsilon_{i,t}$, they are also assumed to be normally distributed, following p-order Autoregression, i.e.,

$$\varepsilon_{i,t} = \psi_{i,1}\varepsilon_{i,t-1} + \psi_{i,2}\varepsilon_{i,t-2} + ... + \psi_{i,p}\varepsilon_{i,p} + u_{i,t} \tag{4.3}$$

Where $Eu_{i,t} u_{j,t-s} = \sigma_i^2$ for i = j and s = 0, 0 otherwise.

Here all the corresponding innovations, u_t and $u_{i,t}$, i=1,…,N, are also assumed to be zero mean, contemporaneously uncorrelated normal random variables.

There are two related identification problems in the model (4.1) - (4.3) should be noted here. Neither the signs nor the scales of the factors and the factor coefficients are identified separately. Therefore, first of all, the signs are identified by requiring one of the coefficients for the each factor to be positive. In particular, I handle this by require the factor coefficients for the global factor are positive. Secondly, the scales are identified by following Sargent and Sims (1977) and Stock and Watson (1989, 1993) to assume that each variance of u_t is equal to a constant. Here I follow the convention by normalizing the variance of u_t to be unity.

Thus, the comovements across countries can be mediated by the common global factor. Through this factor analysis, we are able to measure the impact of both global factor and country-specific factor on the volatility of each country's stock market as well as on its macroeconomic fluctuations. Since the dynamic factor is not observable, analysis of the systems could not be as straightforward as in the general econometrics regressions. In the conventional method, a state space model can be estimated by using the Kalman filter to derive sample log likelihood conditional on the unknown parameters. In the likelihood function, it is maximized numerically with respect to the parameters until convergence, in order to extract all these parameters. However, in this essay, with a large number of factors in the equation, the Kalman filter can become computationally rather burdensome. Therefore, in this study I use the method of Markov Chain Monte Carlo (MCMC) to estimate the posterior distribution of unobserved factors and the parameters, which has been widely used by Chib and Greenberg (1996), and Aguilar and West (2000), among others.

In this essay, I take advantage of Bayesian Gibbs sampling procedure allowing us to estimate a large state space system with a large number of unknown factors and parameters. In Bayesian econometrics, unknown parameters are usually treated as random variables followed by underlying stochastic distribution. Here the prior on all the factor distribution is N(0,1). Given appropriate prior distributions and arbitrary starting values for the model's parameters, Gibbs-sampling can be implemented by the successive iteration of the following three steps: Firstly, I generate the posterior distribution of the factors conditional on the data and prior parameters of the model. Secondly, I generate the parameters ϕ from the conditional distribution conditional on the dynamic factors. Thirdly, I generate ψ_i , λ_i , σ_i^2 based on the equations (4.1)-(4.3) conditional on the data and dynamic factors for country i. Steps 2 and 3 are carried out by using independent Normal-Gamma priors. All the steps are iterated S times, in which the first S_1 draws are discarded as burning-in replications to remove the effect of initial values. Under the regularity conditions satisfied here, I can produce the convergence of Markov Chains and generate the unobserved factors and unknown parameters.

4.2.2 Vector Autoregression (VAR) Model

By employing Bayesian dynamic latent factor model mentioned in above section 4.2.1, I can estimate the dynamic global factors for stock market returns as well as for different macroeconomic variables. These global factors are designed to measure the common movements across countries, and can therefore be used as proxies for the global stock market comovements and global macroeconomic shocks. I argue that the linkage among global stock markets and a set of main macroeconomic variables in a global framework can be realized through investigating the relationship of these global factors. Therefore, the objective can be achieved by estimating a VAR system composed of global macroeconomic shocks and global factor which measure the comovements of global stock markets.

The VAR analysis provides us broad information of the relationship of endogenous variables. For a set of n time series variables $y_t = (y_{1t}, y_{2t,}, ..., y_{nt})'$, the VAR model with p-order can be written as:

$$y_t = A_0 + \sum_{l=1}^{p} A_l y_{t-l} + \varepsilon_t \qquad (4.5)$$

Where p is the lag length; y_t is a (nx1) column vector of variables; A_0 is the constant vector; A_l 's are (nxn) coefficient matrices and $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, ..., \varepsilon_{nt})'$ is an unobservable i.i.d. zero mean error term, i.e., $E(\varepsilon_t) = 0,$ $E(\varepsilon_t^2) = \sigma^2,$ and $E(\varepsilon_t, \varepsilon_s) = 0,$ for $t \neq s$.

In this study, VAR analysis is employed to investigate the relationship between macroeconomic factors and stock market. The lag length in the model is chosen on the basis of the AIC criterion. Variance decomposition and impulse response analyses are also conducted to measure how and to what extent different endogenous variables impact one another in the VAR system. With this in mind, it is helpful to trace the relationships of endogenous variables in the system. Furthermore, it is beneficial to take a closer look at how the change in a variable is due to its own shocks, as well as to the shocks from other variables.

4.3 Data and descriptive statistics

4.3.1 Data of stock markets

The dataset consists of monthly national stock market indices from January 1995 to December 2009 in a group of 34 economies.[29] The dataset is chosen because it can help us to maximize the

29 The countries included in this study are mainly from Asia-Pacific Economic Cooperation (APEC) and European Union (EU). This is because a wide variety of theoretical and empirical studies provide the evidences of the increasing economic and financial integrations in these regions. The EU was established in November, 1993. Although APEC was established in 1989, economic progress of free and open trade and investment in the Asia-Pacific region was not achieved until a 1994 meeting in Bogor, Indonesia, when the so-called Bogor Goals were met.

number of countries in this study, as not all countries have the data of stock market and macroeconomic variables over a longer period. In particular, the data of short-term interest rates is not available among several countries before 1993. Furthermore, considering the limitation of the availability of macroeconomic variables, monthly data is the best observation of stock market fluctuations. The monthly data is more successful at capturing the fluctuations of stock market than the quarterly and annual ones as stock markets are frequently fluctuated. Finally, since this study focuses on the economies in APEC and EU regions, it better allows us to study the global factors and international comovements because of the increasing globalization and financial integration in these regions since the mid-1990s.

Monthly data for stock markets consists of the closed price indices expressed in local currency. The data are obtained from Datastream International. I follow the conventional method to calculate the monthly returns of stock market for country i at time t, i.e.:

$$R_{i,t} = 100 * (\log p_{i,t} - \log p_{i,t-1}) \tag{4.5}$$

Where i refers to stock market, t to month; $R_{i,t}$ represents the stock market returns; $p_{i,t}$ is the stock market price index in local currency, all in month t for country i. Instead of choosing the price index $p_{i,t}$ in a fixed date as the monthly data for stock market, here I use the average of price index in order to eliminate the excess volatilities of price. The price benchmark is to calculate the average price indices in all trading dates in each entire month.

Before estimation, one concern with the procedures is whether or not the larger stock markets have more power in affecting the global factors solely because of their big market sizes. In this study, I use the stock market returns, which are actually the changing rate of stock price index, so the size of stock market has no direct impact on the research of stock market commovments. I adhere to this in the study by ensuring that all the series have equal weight irrespective of their relative market sizes in the world.

4.3.2 Data of macroeconomic fundamentals

In this study, the selection of macroeconomic variables is based on theoretical propositions and existing evidence in the literature. I appeal to economic and financial theories and previous empirical evidences to select the potential macroeconomic variables. As financial theories and studies have addressed, macroeconomic factors, such as output, inflation, and money policy are proposed variables.

Previous research has identified the relationship between stock market and real business activity. For one, many studies find that real economic activity is the most important factor influencing the fluctuation of stock market (Fama, 1990; Chen et al., 1986; Schwert, 1990; and Lee, 1992, among others). Thus, industrial production is included as a proxy for real economic activity and macroeconomic development factor in this study.

Secondly, changing inflation may also affect stock market through the channel of changing the discount rates. A higher inflation would increase the discount rate and then lower stock market returns. Fluctuations and uncertainty about fundamentals are also potential factors affecting the stock market. For example, inflation and earnings uncertainty are identified as the sources of the fluctuation of stock market returns (Lee, 1992; and Boudoukh and Richardson, 1993). Therefore, I also consider the measures of macroeconomic shocks to account for the uncertainty of inflation factor. Specifically, I construct a proxy for monthly year-to-year inflation on the basis of the Consumer Price Index (CPI).

Finally, money policies may affect stock market through various channels. Take for instance the money supply. An increase in money supply would lead to inflation and thus negatively affect stock market returns. On the other hand, an increase in money supply may lower the interest rates which could in turn bring firms more investment opportunities and decrease discount rates. According to the so-called “fisher effect” expected nominal rates of interest on financial assets should move one-to-one with expected inflation. Moreover, changes in both short term and long term interest rates are expected to impact the discount rate through their effect on nominal risk-free rate (Mukherjee and Naka, 1995; and Lee, 1992). Interest rates are also expected to be directly related to stock market through either inflationary or discount factor effects. Therefore, I use short-term interest rate as a proxy for monetary policy in this analysis.[30]

In sum, I construct the following macroeconomic variables in this study: industrial production growth rate (IP), inflation rate (Inflation), and short-term interest rate (Interest).[31] Logarithmic differences are taken to measure the changing rates of the first two variables. I follow the approach suggested by James et al. (1985) to measure these macroeconomic variables, i.e., year-to-year industrial production growth and CPI changing rate which, by construction, have no seasonal patterns. For consistency with the measurement of the macroeconomic variables, stock market returns are multiplied by 12 to make them annual. Table 4.1 presents the description of all variables in this study: their symbols, calculation methods, and data sources.

<Tables 4.1 and 4.2 here>

The summary statistics of monthly stock market returns across countries are presented in Table 4.2.[32] As expected, real returns of emerging markets are, on average, smaller but more volatile than those of developed markets. Interestingly, real returns for most markets are positive, while nominal returns are all positive with exception of Japan and Thailand. The most likely reasons for the negative returns in these two countries is Thailand's substantial economic downturn during following 1997 Asian crises and Japan's persistent economic depression since the early 1990s.

4.4 Empirical results

30 Some alternative measure of monetary policies such as money supply M2 is also supposed to be consider in the model. However, the monthly data is not available for a large group of countries in the sample because of the limitation of data resources.

31 Money market interest rates are used as the substitute of short-term interest rates because of unavailability of that data in a few countries.

32 For saving space, the descriptive statistics for macroeconomic variables across countries are not reported here.

In the implementation of this study, for simplicity and for saving the degree of freedom, I assume that both the lengths of idiosyncratic terms and factor autoregressive polynomials are 2. It should be noted that the model, in principle, works well for the general case of AR (p) autoregression. Gibbs-sampling can be implemented by successive iteration of the three steps discussed in Section 4.2, given appropriate prior distributions and arbitrary starting values for the model's parameters. The simulation has been iterated in different lengths ranging from 5,000 to 30,000. The Gibbs sampler converges to the same results if the iteration is greater than 5,000. In this study, I report the results of the Gibbs sampler with iteration 25,000 times, in which the first 5000 draws are discarded as burning-in replications to remove the effect of initial values.

4.4.1 International stock market Comovements and global macroeconomic factors

4.4.1.1 Dynamic global factors

<Figure 4.1 here>

Figures 4.1.1 through 4.1.5 present the median of the posterior distribution of global factors for industrial production, inflation rate, interest rates and stock market real and nominal returns across countries, respectively. First of all, Figure 4.1.1 presents the median of the posterior distribution of global factor for industrial production. The fluctuations in the factor well describe the major global economic activities in the recent 15 years: the recession from mid-1997, associated with the Asian financial crisis; and the downturn of early 2000, associated with the IT bubble that began in the United States early 2000, and also associated with the impact from the September 11 attacks in 2001. In particular, the deepest trough in the figure reflects the recent economic recession from 2007 to 2009.

The common inflation movements across countries are reported in Figure 4.1.2. The dynamics and trends in the global inflation really reflect world-wide inflation events over the past 15 years. The global factor of inflation generates the fluctuation around zero except for two troughs, suggesting that the world showed small waves of inflation and deflation in most periods.

However, there are two exceptions. The first is from 1995 until 1999. This time frame is associated with the decline of economy and tight monetary policies and financial crises during these periods. The second trough is associated with economic recession in recent two years from 2008 until 2009. Here, the findings are very consistent with those of Ciccarelli and Mojon (2010).[33]

Furthermore, Figure 4.1.3 presents the global impacts on the monetary policy through the channel of interest rates. The global monetary factor displays a strong downward trend starting in mid-1995. The first trough is reached in mid-1999. After that, it follows an upward trend for one and half year, and then continues to display a strong downward trend from late 2000 to 2005. Interestingly, the significant fluctuations as characterized by negative values reflect the decreasing interest rates of the time.

Finally, Figures 4.1.4 and 4.1.5 present the median of posterior distribution of global factors for stock market real and nominal returns across economies in the world. Similarly, as shown in the figures, the dynamics of global factor vividly illustrate the major global stock market shocks over the last 15 years. Among them, there are several significant troughs that clearly characterize the major global market shocks. For example, the Asian Financial Crisis, which started in July 1997, raised the fears of a worldwide stock markets meltdown due to financial contagion. Additionally, most stock markets in industrialized economies were greatly affected when the "IT bubble" started in the early 2000s in the United States. The stock market was then negatively impacted in 2001 following the September 11 attacks. Subsequently, after recovering from lows reached during that time period, the stock market downturn of 2002 dramatically impacted the economies of a large group of countries, including the United States, Canada, Asia, and Europe. Most recently, the 2007-2009 markets crash impacted economies across the globe, making it the disastrous financial crises over the recent decades. The steepest drops of factor dynamics in this figure are consistent with the disastrous market downturn of 2008 cross countries in the world.

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33 Ciccarelli and Mojon (2010) use quarterly data to study the global inflations among main OECD countries between 1960:1 and 2008:2 by employing dynamic factor model. My findings relating to the pattern of global inflation is similar to their findings during the common period from 1995 to 2007.

4.4.1.2 Variance decomposition analysis of dynamic factors

To measure relative contribution of global factor to the variation of macroeconomic variables and stock market returns, I estimate the share of the variance of each variable due to different factors. I decompose the variance of each variable into the global factor and country idiosyncratic component. Since these two factors are orthogonal, the variance of $y_{i,t}$ for country i can be written as:

$$\operatorname{var}(y_{i,t}) = \lambda_i^2 \operatorname{var}(f_t) + \operatorname{var}(\varepsilon_{i,t}) \tag{4.6}$$

Based on equation (4.6), I estimate the share of the variance of each variable attributable to these two factors. Therefore, I can investigate to what extent the global and country-specific idiosyncratic factors affect the variation of each variable. They are expressed as follows:

$$S_i^{world} = \frac{\lambda_i^2 \operatorname{var}(f_t)}{\operatorname{var}(y_{i,t})}; \quad S_i = \frac{\operatorname{var}(\varepsilon_{i,t})}{\operatorname{var}(y_{i,t})}; \tag{4.7}$$

Where i=1,…, N for country i; and S_i^{world} and S_i represent the shares of global factor and country idiosyncratic component for the variation of each variable in country i, respectively.

<Tables 4.3 and 4.4 here>

Table 4.3 presents the variance shares of national series attributable to the global factor for macroeconomic fundamentals, as well as stock market returns across countries. Similarly, Table 4.4 presents the average of variance shares for both pooled countries and developed countries, respectively.

First of all, the global factor, on average, accounts for approximately 50% of the fluctuations of countries' industrial output. Among them, the global factor can explain more than 50% of the fluctuations in 13 out of 33 countries, particularly in developed countries such as

75.91% in Austria, 76.25% in Japan, 79.17% in Belgium, 79.68% in the USA, 83.69% in Sweden, 84.62% in Spain, 86.25% in Germany, 86.26% in Finland, 86.95% in France, 86.97% in the United Kingdom, and 88.03% in Italy. Furthermore, in terms of the results of the average of variance shares attributable to global factor in Table 4.4, I find that the global factor can explain around 56.12% of the fluctuations of industrial output in developed countries.

Secondly, the global factor, on average, can explain more than one-third of country's inflation fluctuations. Among 16 out of 34 countries, the global factor accounts for more than 40% of the inflation fluctuations. Following the comparison analysis above, I find that the global factor, on average, explains around 43.42% of the inflation fluctuations in developed countries. However, I find no evidence that the global factor has significant effects on the individual country's inflation fluctuations in South America. For example, the global factor only explains a very small portion of national inflation fluctuations in some countries, such as 0.60% in Argentina, 0.66% in Mexico, 1.53% in Brazil, and 4.10% in Peru. In contrast, a high degree of inflation rate comovements can be found across European countries for the implementation of monetary union in this region. In Europe, the global factor accounts for a large portion of individual country's inflation fluctuations, such as 62.10% in Germany, 67.69% in Belgium, 67.92% in France, 71.60% in Austria, 76.19% in Switzerland, and 81.10% in Spain.

Thirdly, there exist strong comovements of interest rates across countries, which are consistent with the findings in recent studies (see Henriksen et al., 2009; Diebold et al., 2008; and Byrne et al., 2010, among others). Generally, the global factor accounts for a substantial fraction of the interest rate fluctuations in developed countries, whereas a very small in some emerging countries. For example, the global factor only explains 0.01% of interest rates fluctuations in Argentina and 3.78% in Indonesia. This indicates that the fluctuations of interest rates in these countries are mainly driven by their own characteristics, instead of by the global factor. Interestingly, as shown from column four in Table 4.3, the global factor accounts for around 91.76% of the Euro fluctuations. This demonstrates that the Euro currency is strongly co-moved with the global monetary market.

Finally, columns five and six in Table 4.3 present the variance shares attributable to the global factors for each individual country's stock market real returns as well as nominal returns.

The results show that the degree of the comovements of global stock markets is much higher than that among macroeconomic fundamentals discussed above, for the global factor has a more explanatory power of accounting for the fluctuations, whether averaging the countries as a whole or individually. For example, the global factor can, on average, account for around 56 percent of the country's stock market volatility. In particular, the global factor, on average, explains around 66 percent of the stock market volatility in the developed countries. In terms of the results for each individual country, the global factor can explain more than 50% of the stock market volatility in 19 out of 34 markets in my sample. In particular, the global factor accounts for a significantly large portion of the variations of stock market real returns in developed markets: for example 81.11% in the United Kingdom, 81.24% in the United States, 83.68% in Germany, 87.02% in France, and 90.82% in Netherlands. All these indicate that there exists a high degree of stock market comovements across economies, especially in developed markets.

4.4.2 Measuring the effects of global macroeconomic factors

As argued in the above section, here I will employ the VAR analysis to measure the effects of global macroeconomic factors on the price movement of the global stock markets as well as that of each individual stock market. There are two main purposes in this subsection: the first aims to investigate how the global macroeconomic shocks have effects on the movements of global stock markets in a global perspective; the second aims to investigate to what extent each individual country's stock market will respond to the global macroeconomic shocks and its own macroeconomic fluctuations.

4.4.2.1 Empirical results of VAR analysis

To address the first issue, I employ the VAR analysis to answer it. Before I begin this analysis, I first employ a preliminary Pearson correlation analysis to examine the relationship between global macroeconomic factors and global stock market movements. The correlation results are reported in Table 4.5. Interestingly, the results show that industrial production is weakly but positively correlated with both real and nominal stock market returns. However, the inflation is significantly and negatively correlated with both real and nominal stock market returns, and the interest rate is also negatively correlated with them, but weakly.

<Table 4.5 here>

These findings together make us even more curious about the interactions among global macroeconomic factors and global stock market movements. Therefore, I precede a VAR analysis to have a detailed examination of their relationship. The presence of the common shocks and comovements among the variables implies that the ordering is important. Based on the literature and the following models of Balvers et al. (1990), Canova and De Nocolo (1995) and Cochrane (1991), it is reasonable that industrial production factor is placed first, followed by inflation factor, interest rate factor.

<Table 4.6 here>

In this analysis, my main intent aims to understand how the main global macroeconomic factors affect international stock market movements. Therefore, I present only the results of the effects of global macroeconomic factors, represented by industrial production, inflation, and interest rates, on stock markets from the VAR analysis in Table 4.6. The results show that international stock market movements is positively correlated with industrial production factor, which is consistent with those findings in a variety of previous studies that there is a positive effect of industrial output on stock market returns (see Chen et al., 1986; Fama, 1990; Canova and De Nicolo, 1995; and Lamont, 2000, among others), for the innovation of industrial production can be linked to the changing expectations of future cash flow (Balvers et al., 1990). Furthermore, the results show that global inflation has negative effects on international stock market movements. The finding demonstrates that the inflation directly influence stock market returns (negatively), which is also consistent with previous studies (see Chen et al., 1986; Fama, 1990; and Boudoukh and Richardson, 1993, among others). Inflation can affect the discount rate, thus reducing the present value of future corporate cash flows. The rising inflation also initially negatively affect corporate income due to the immediate rising costs and adjusting output prices, causing the profits decline and therefore, the stock prices decline. Therefore, the global inflation has negative impact on the international stock markets. Finally, in terms of monetary policy, results show that stock market movements are negatively related with global interest rate factor.

The negative response is consistent with the findings in previous studies (see Bulmash and Trivoli, 1991; and Mukherjee and Naka, 1995), as interest rates can affect stock market movements through two channels: endogenous response to macroeconomic activity and through discount rate. On the one hand, interest rate innovation could be the driving force in determining industrial production (due to changes in investment), which might affect stock market returns as argued above. On the other hand, interest rate innovations could also directly influence stock market returns through the channel of discount rate since a change of discount rate can affect present value of future cash flows and then the cumulative sum of income and returns.

To further understand the role regarding how the global macroeconomic fundamental shocks influence the volatility of global stock markets, variance decomposition is also conducted on the basis of the VAR analysis above and hence can address the effects of global macroeconomic fundamentals on the fluctuations of global stock markets.

<Table 4.7 here>

Table 4.7 presents the results of variance decompositions after one, three, six, and twelve months for the explanatory variables. Global market own movements are the major role in effecting the global stock market volatility, explaining from 86.71%, 80.09%, 71.99%, and 66.09% of the variance after one, three, six, and twelve months, respectively. However, global macroeconomic factors, represented by global output factor, global inflation factor, and global interest factor, explain 13.29%, 19.91%, 28.01%, and 33.91% of the variance after one, three, six, and twelve months, respectively. Among global macroeconomic fundamentals, the global interest factor explains the largest part of the variance of global stock markets after one month, taking 7.64%. However, the global inflation factor plays the major role in affecting the variation after twelve months, explaining 16.66% of the forecast variance, followed by the global output factor with 9.46% and the global interest factor with 7.79%.

4.4.2.2 Individual country's stock market and global macroeconomic factors

To address the second question regarding how an individual country's stock market will respond to the global macroeconomic shocks and its own macroeconomic fluctuations, I conduct the

VAR analyses in two different cases for each country in my sample: the first is the VAR system consisting of the country's own macroeconomic fluctuations, global macroeconomic factors, and stock market returns; the second is the one consisting only of its own macroeconomic fluctuations and stock market returns without including global macroeconomic factors.

<Table 4.9 here>

Table 4.9 presents the R^2 statistics in the VAR analysis for each country's real stock market returns in both cases.[34] The R^2 statistic is a measure that can give some information about the goodness of fit of a model. I find that in most countries the R^2 values are significantly increased in the VAR analyses consisting of the global macroeconomic factors. On average, the results show that there is an increase of more than 50 percent in the R^2 values for both pooled and developed markets. In particular, the R^2 statistics are greatly increased in developed markets; for example from 0.240 to 0.411 in Hong Kong, from 0.111 to 0.318 in Japan, from 0.081 to 0.191 in the United Kingdom, and from 0.280 to 0.440 in the USA. The R^2 statistics reported in Table 4.9 imply that a standard F-test would reject the zero coefficients on the global macroeconomic factors for many countries in these regressions. Therefore, I argue that it would be more reliable to include the global macroeconomic shocks when investigating the relationship between macroeconomic fundamentals and an individual country's stock market movements.

<Table 4.10 here>

Therefore, variance decomposition on the basis of the VAR analysis in the first case is conducted to have a further look at how an individual country's stock market volatility is associated with the global macroeconomic shocks and its own macroeconomic fluctuations. Table 4.10 presents the results of variance decompositions after twelve months on the basis of the VAR analysis. The results in Table 4.10 show that global macroeconomic factors, represented by global industrial production, global inflation, and global interest factor, on average, explain 20.59% of the individual country's stock market fluctuations after twelve

34 For saving the space, the results of VAR analysis and variance decompositions for all these individual countries are not reported here. The detail results can be available upon request.

months. In most developed economies, the global macroeconomic factors account for a larger portion of the country's stock market fluctuations than their own macroeconomic fluctuations do, particularly in prominent countries such as Australia, Canada, Japan, Portugal, Switzerland, and the USA. However, in several emerging economies, the stock market movements are driven more by their own macroeconomic fluctuations than by global macroeconomic factors.

All these findings indicate that the global macroeconomic shocks have strong effects on the movement of global stock markets as well as that of individual stock markets. In most developed economies, the global macroeconomic shocks accounts for a larger part of the forecast variances of individual stock markets than their own macroeconomic shocks. These results suggest that in an increasingly integrated global economy, we have to look beyond national borders in order to correctly identify and measure the underlying macroeconomic risks in financial markets. We may miss important sources of macroeconomic risks if we only use domestic macroeconomic variables in our empirical studies.

4.4.3 Does market integration reflect economic integration?

In the previous section, the results show that there are some differences in financial-market integration across developed and emerging markets. The findings also indicate that the global macroeconomic shocks play different roles in driving the price movements of stock markets in different economies. Thus, I am curious whether and to what extent market integration is associated with economic integration in the world. In the literature, Bekart and Harvey (1995) and Bhattacharya and Daouk (2002) provide evidence that certain variables might be linked to the information of the dynamics of integration. Carrieri et al. (2007) also indicate that financial market development and financial linearization policies play important roles in the integration of emerging markets. However, these examples in the literature are nonetheless vague as there are no comprehensive theories and empirical studies that specifically address this issue.

As shown above, the variance shares of global factor can be used to measure the degrees of integration of financial markets across countries as well as those of global macroeconomic fundamentals, represented by industrial production, inflation, and interest rate. To address this, I investigate the relationship between these variance shares of global factors. Therefore, it is possible to explore whether and to what extent the market integration reflects economic integration.

<Table 4.8 here>

Column one in Table 4.8 presents the "impact" coefficients of real returns for different countries. The result presents the differences of each individual country's exposure to the global stock market risk. The coefficients range from 0.793 to 2.193 in the sample, indicating that the global factor plays different roles the fluctuation of each individual stock market.

To better understand the evolution of market integration and the corresponding exposure to global market risks, I use the variance shares of global factor for the real returns $S_{i,\mathrm{Re}al}^{world}$ estimated above as the dependent variable. In this analysis, I estimate the regression of $S_{i,\mathrm{Re}al}^{world}$ on the variance shares of global macroeconomic factors for both pooled and developed countries. The equation is written as:

$$S_{i,\mathrm{Re}al}^{world} = \beta_0 + \beta_1 S_{i,IP}^{world} + \beta_2 S_{i,Inflation}^{world} + \beta_3 S_{i,Interest}^{world} + \varepsilon_i \tag{4.8}$$

<Table 4.11 here>

In this analysis, it can help us investigate to what extent market integration is associated with the macroeconomic fundamentals integration in the world. Table 4.11 presents the estimates and the R^2 statistics of the regression for 32 pooled and 24 developed economies, respectively.[35] There is no significant difference between these two samples. In both cases, the estimated coefficients are large and positive, indicating that the degree of market integration is associated with the degree of the integration of global macroeconomic fundamentals. Among the three coefficients, only the estimated coefficient of global inflation is significant, but not for the other two.

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35 Countries of Philippines and Taiwan are not included here since the data of industrial production for Philippines and interest rates for Taiwan are not available.

<Figure 4.2 here>

To better understand the goodness of the fit of the model, in Figure 4.2 I plot the relationships between the actual values and the fitted values for both pooled countries and developed countries. The actual values are from the variation shares of global factor for stock market real returns, and the fitted values are estimated on the basis of the regression. The results show that the fitted line works well for most countries. As shown in the figures, the fitted values well reflect the actual ones of market integration. The findings also indicate that the level of market integration is really associated with the level of economic integration in the world, especially in developed countries. For example, based on the analysis in this study, the USA, the United Kingdom, Germany, France and the Netherlands are the five most integrated markets in the world, with the global factor accounting for substantial fractions of stock market volatility at 81.11%, 81.24%, 83.68%, 87.02%, and 90.82%, respectively. Apparently, all five of these economies are among the most economically integrated and developed in the world. Therefore, I argue that, in a partially integrated global economy, a country's exposure to the global stock market risk can be largely explained by that country's exposure to the global macroeconomic risks.

4.5 Robustness test

I consider the robustness of the results with respect to examination of stock market nominal returns instead of real returns as above. Further, I also extend the study to allow for a different group sample group, such as OECD countries.

<Table 4.12 here>

First of all, I want to check whether the relationship between macroeconomic factors and stock market would be altered if the nominal returns were employed instead in the analysis. By using the nominal returns rather than the real returns in above section, I find a very similar pattern for the relationship between macroeconomic factors and stock market, which are reported in Table 4.12. From the variance decomposition analysis by employing nominal returns, I produce slightly higher contribution of inflation for the variation of market returns.

<Table 4.13 here>

Secondly, the above investigations are based on the main countries in APEC and EU, which represents the studies for developed and developing countries together in a global perspective. I shall expect that under the same market integration scenario, the relationship between macroeconomic variables and stock market, should demonstrate similar patterns among those OECD countries. Therefore, I conduct the robustness tests by using the data from the main OECD countries. The results are presented in Table 4.13. The results show that the global macroeconomic factors play the similar roles in driving the comovements of international stock markets returns.

Thirdly, instead of study the interrelationship in a global perspective, I also want to investigate whether the constancy of the relationship between macroeconomic variables and stock market works in individual country. For example, I choose USA, which a lot of previous studies have investigated and Germany, which is more strongly linked to other European continental economies than other countries since the sample countries in the analysis above are mainly from European Union.[36] The results show that the relationship in these two typical countries has the same pattern with those previous results of the relationship I have.

In sum, my main findings are robust for market integration based on the relationship between macroeconomic variables and stock market. Using different measures of stock returns, including the real and nominal returns, I find that the results do not change. And even when the data is adopted from a different source (OECD) in the analysis, it turns out that the results are similar to I have for pooled countries. Given these two concerns, the results discussed above can be served as a robustness check for the relationship between macroeconomic variables and stock market in a global perspective. This investigation can also be extended to study the same

36 For saving the space, I do not report the results of VAR analysis and variance decompositions for countries of USA and Germany here. The detail results can be available upon request from the authors.

relationship in some individual countries, and I find that the relationship between macroeconomic variables and stock market does not change.

4.6 Conclusion

In the context of a partially integrated global economy, I am particularly interested in the relationship between international stock market movements and the underlying macroeconomic fundamentals. I investigate global stock market integration by incorporating the underlying macroeconomic fundamentals across a large group of countries with two main objectives. The first aims to investigate how and to what extent the global macroeconomic shocks impact the price movement of the global stock market as well as that of an individual market. The second focuses on the investigation of the relationship between the degrees of market integration across countries and those of their own economic integration and thus, can help us better understand whether a country's exposure to the global market risk is associated with that country's exposure to global macroeconomic risks.

In this study, I employ a framework of several economical models to study a group of 34 countries over the years 1995-2009, covering main developed and emerging economies in both APEC and EU regions. I use Bayesian dynamic factor models to decompose stock market returns and other major macroeconomic variables into common global and idiosyncratic country-specific factors. My main findings are summarized as follows.

Firstly, when I examine both international stock market comovements and world business cycles, the findings are similar to the results in previous studies in the literature. I find that there is a significantly common global factor present in the fluctuations of all variables in almost all of the countries in the sample. Further variance decomposition analysis shows that the global factor accounts for a substantial fraction of stock market volatility as well as the macroeconomic fundamental fluctuations in most economies. In particular, on average, the global factor, can explain more than 66 percent of a country's stock market fluctuations in developed economies. Interestingly, the findings also indicate that the degree of the comovements of international stock markets is much larger than that of main macroeconomic fundamentals. All these together indicate that there exists a high degree of international market integration, especially in the developed economies.

Secondly, when I measure the effects of global macroeconomic factors on the price movement of global and each individual stock market, I find that the results indicate that the global macroeconomic shocks have strong effects on the price movement of global stock market as well that of an individual market. I also find that a country's stock market movement is driven more by the global macroeconomic shocks than by their own macroeconomic fluctuations in most developed economies. These results suggest that in an increasingly integrated global economy, we have to look beyond national borders in order to correctly identify and measure the underlying macroeconomic risks in financial markets. We may miss important sources of macroeconomic risks if we only use domestic macroeconomic variables in our empirical studies.

Lastly, I address the relationship between market integration and economic integration in a global framework. In a partially integrated global economy, I find that strong financial market integration exists across countries along with their own strong economic integration in the world, especially in developed economies. The results indicate that the degree of a country's market integration is closely related with the degree of its own economic integration in the world. In another words, a country's exposure to the global stock market risk can be largely explained by that country's exposure to the global macroeconomic risks.

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Appendix

A1: MCMC Approach to Dynamic factor Analysis

In this implementation in this study, for simplicity and also for saving the degree of freedom, both the idiosyncratic and common factors are assumed to follow the 1-order autoregression. It should be noted that the model, in principle, works well for general case of AR(*p*) autoregression. I also assume that the priors on all the factor loading coefficients are random variables.

For the ease of the reference, I stack the state vectors and parameters together. Therefore, the following notations are employed:

$$\tilde{R}_T = [R_1, R_2, ..., R_T]', \quad \tilde{Y}_T = [y_1, y_2, ..., y_T]', \; \tilde{F}_T = [f_1, f_2, ..., f_T]', \; R_t = [R_{1,t}, R_{2,t}, ..., R_{N,t}]',$$

$$y_t = [y_{1,t}, y_{2,t}, ..., y_{N,t}]', \text{ And } \; f_t = [f_t^{world}, f_{1,t}^{region}, f_{2,t}^{region}, ..., f_{R,t}^{region}]'$$

So the equation (1.1)-(1.3) can be changed as the following equations.

$$R_{i,t} = \mu_i + b_i^{world} f_t^{world} + b_i^{region} f_{r,t}^{region} + \varepsilon_{i,t} \tag{A.1}$$

$$f_t = \phi_1 f_{t-1} + u_{f,t} \tag{A.2}$$

$$\varepsilon_{i,t} = \psi_{i,1}\varepsilon_{i,t-1} + u_{i,t} \tag{A.3}$$

Where

$$\phi_1 = \left[\phi_1^{world}, \phi_{1,1}^{region}, \phi_{2,1}^{region}, ..., \phi_{R,1}^{region}\right]', \; u_{f,t} = [u_t^{world}, u_{1,t}^{region}, u_{2,t}^{region}, ..., u_{R,t}^{region}]'.$$

In terms of the above assumptions and the stacked notations, I stack the model in equation (2.1) as the following state-space form:

$$y_t = Bf_t + \varepsilon_t, \tag{A.4}$$

$$f_t = Hf_{t-1} + v_t \tag{A.5}$$

Where $y_t = R_t - \mu$ are the de-meaned returns at month t, R_t denotes the N×1 vector of stock market returns and f_t denotes the K×1 vector (K=R+1) and, B is a N×K matrix of b's, and v_t denotes the K×1 vector of idiosyncratic shocks.

The specification cans be written as follows:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \\ \dots \\ y_{Nt} \end{bmatrix} = \begin{bmatrix} b_1^{world} & b_1^{region} & 0 & \dots & 0 \\ b_2^{world} & b_2^{region} & 0 & \dots & 0 \\ b_3^{world} & 0 & b_3^{region} & \dots & 0 \\ \dots & \dots & \dots & \dots & 0 \\ b_N^{world} & 0 & 0 & \dots & b_R^{region} \end{bmatrix} \begin{bmatrix} f_t^{world} \\ f_{1,t}^{region} \\ f_{2,t}^{region} \\ \dots \\ f_{R,t}^{region} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \dots \\ \varepsilon_{Nt} \end{bmatrix}$$

$$\begin{bmatrix} f_t^{world} \\ f_{1,t}^{region} \\ f_{2,t}^{region} \\ \dots \\ f_{R,t}^{region} \end{bmatrix} = \begin{bmatrix} \phi_1^{world} & 0 & 0 & \dots & 0 \\ 0 & \phi_{1,1}^{region} & 0 & \dots & 0 \\ 0 & 0 & \phi_{2,1}^{region} & \dots & 0 \\ 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \dots & \phi_{R,1}^{region} \end{bmatrix} \begin{bmatrix} f_{t-1}^{world} \\ f_{1,t-1}^{region} \\ f_{2,t-1}^{region} \\ \dots \\ f_{R,t-1}^{region} \end{bmatrix} + \begin{bmatrix} u_t^{world} \\ u_{1,t}^{region} \\ u_{2,t}^{region} \\ \dots \\ u_{R,t}^{region} \end{bmatrix}$$

$$E(v_t v_t^{'}) = Q = \begin{bmatrix} \sigma_w^2 & 0 & 0 & \dots & 0 \\ 0 & \sigma_{region,1}^2 & 0 & \dots & 0 \\ 0 & 0 & \sigma_{region,2}^2 & \dots & 0 \\ 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \dots & \sigma_{region,R}^2 \end{bmatrix}$$

and $$E(u_{i,t} u_{i,t}^{'}) = R = \begin{bmatrix} \sigma_1^2 & 0 & \dots & 0 \\ 0 & \sigma_2^2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \sigma_N^2 \end{bmatrix}$$

Where Q and R are the diagonal variance –covariance matrixes.

Suppose we happened to know $\tilde{F}_T$, then the state-space system in (A.4)-(A.5) is easily turned to a set of separate linear regressive equations (2.1)-(2.4) with known explaining variables, of which we can directly use the well-known procedure to estimate them. However, all of them can't be estimated directly. Since it is not, some special methods are employed to estimate them.

According to the Stock and Waston's (1991) and Kim and Nelson (1998) applications of the state space model and the Gibbs sampling to a linear dynamic factor model, the dynamic factor analysis model in equation (2.1)--(2.4) can be considered as the Gaussian probability density for the data {Y_t} conditional on a set of parameters φ and a set of latent variables {f_t}. Call this density function $p_{\mathrm{y}}(\mathrm{Y}|\varphi,\mathrm{F})$ where Y denotes the NT$\times$1 vector of data on the data {$y_{i,t}$}, and F denotes the KT $\times$1 vector of dynamic factors {$f_{i,t}$}. In addition, there is a specification of a Gaussian probability density $p_{\mathrm{f}}(\mathrm{F})$ for F itself. Given a prior distribution for φ, $\pi(\varphi)$, the joint posterior distribution for the parameters and the latent variables is given by the product of the likelihood and prior, $\mathrm{h}(\varphi,\mathrm{F}|\mathrm{Y}) = \mathrm{p_y}(\mathrm{Y}|\varphi,\mathrm{F}).\mathrm{p_f}(\mathrm{F})\ .\pi(\varphi)$.

Here, the conditional density $p(\tilde{F}_T|\tilde{Y}_T)$ could be obtained through a simulation smoother. By employing Carter and Kohn's multimove Gibbs-sampling approach, I generate the $\tilde{F}_T$ from the joint distribution given by (here I temporarily omit the parameters φ, ϕ and σ for the ease of denotation)

$$
\begin{aligned}
& p(\tilde{F}_T|\tilde{Y}_T) \\
& = p(f_T|\tilde{Y}_T)\, p(\tilde{F}_{T-1}|f_T, \tilde{Y}_T) \\
& = p(f_T|\tilde{Y}_T)\, p(f_{T-1}|f_T, \tilde{Y}_T)\, p(\tilde{F}_{T-2}|f_{T-1} f_T, \tilde{Y}_T) \\
& \ldots \\
& = p(f_T|\tilde{Y}_T)\prod_{t=1}^{T-1} p(f_t|f_{t+1}, \tilde{Y}_t)
\end{aligned}
$$

Because the state-space model is linear and Gaussian, the distribution of f_T given $\tilde{Y}_T$ and that of f_t given f_{t+1} and y_t for t=T-1, …, 1 are also Gaussian:

$$
\begin{aligned}
& F_T|\tilde{Y}_T \sim N(F_{\mathrm{T|T}}, P_{\mathrm{T|T}}), \\
& f_t|\tilde{\mathrm{y}}_t \sim N(f_{t|\mathrm{T}}, P_{t|\mathrm{T}}),
\end{aligned}
$$

Where $F_{T|T} = E(F_T|\tilde{Y}_T)$, $p_{T|T} = \text{cov}(F_T|\tilde{Y}_T)$, $f_{t|T} = E(f_t|\tilde{y}_t)$, $P_{t|T} = \text{cov}(f_t|\tilde{y}_t)$

Therefore, I can directly compute the $f_{t|T}$ and $P_{t|T}$ by using the Gibbs Sampling and smoother algorithm with initial values $f_{1|0}$ and $P_{1|0}$,

$$f_{t|t} = f_{t|t-1} + P_{t|t-1}B^{'}(BP_{t|t-1}B^{'} + R)^{-1}(y_t - Bf_{t|t-1})$$
$$P_{t|t} = P_{t|t-1} - P_{t|t-1}B^{'}(BP_{t|t-1}B^{'} + R)^{-1}BP_{t|t-1}$$

The above Kalman filter runs forward with t=1, 2, …, T and backward with t=T-1, T-2,…, 1. For a rigorous derivation, the argument can be found in chapter 3 of the Kim and Nelson (1999) book.

Gibbs-sampling can be implemented by successive iteration of the following three steps, given appropriate prior distributions and arbitrary starting values for the model's parameters:

Step 1: Conditional on all the data ($\tilde{Y}_T$) and all the parameters of the model, generate the dynamic factors $\tilde{F}_T$;

Step 2: conditional on the dynamic factors $\tilde{F}_T$, generate $\tilde{\phi}$ based on equation (A.2);

Step 3: conditional on the dynamic factor $\tilde{F}_T$ and the data ($\tilde{Y}_T$) for the i-th stock market data, generate $\tilde{\psi}_i$, b_i, σ_i^2 based on the equation (A.1) and (A.3);

The detail procedures for the Gibbs-sampling mentioned in above three steps can be detailed as follows:

Step 1: Generate the dynamic factors $\tilde{F}_T$, Conditional on all the data ($\tilde{Y}_T$)

To do this part, I need to put the model in a state-space form. By simply multiplying both sides of (2.1) with $\psi_i(L) = 1 - \psi_{i,1}$, $i = 1, 2..., N$, I could turn the equation (2.1) into the following equations:

$$\psi_i(L)y_{i,t}=\psi_i(L)b_i^{world}f_t^{world}+\psi_i(L)b_i^{region}f_{r,t}^{region}+\psi_i(L)\varepsilon_{i,t} \qquad \text{(A.6)}$$

Then, the state-space representation is given by Measure Equation as follows:

$$y_{i,t}^{*}=b_i^{world}f_t^{world*}+b_i^{region}f_{r,t}^{region*}+\varepsilon_{i,t}$$

$$E(\varepsilon_{i,t}\varepsilon_{i,t}^{'})=R=\begin{bmatrix}\sigma_1^2 & 0 & ... & 0\\ 0 & \sigma_2^2 & ... & 0\\ ... & ... & ... & ...\\ 0 & 0 & ... & \sigma_N^2\end{bmatrix}$$

Where $y_{i,t}^{*}=y_{i,t}-\psi_{i,1}y_{i,t}$, $f_t^{world*}=f_t^{world}-\psi_{i,1}f_{t-1}^{world}$, and $f_{r,t}^{region*}=f_{r,t}^{region}-\psi_{i,1}f_{r,t-1}^{region}$ $i=1,2...,N$

Step 2: Generate $\tilde{\phi}$, conditional on the dynamic factors $\tilde{F}_T$

Conditional on $\tilde{F}_T$ equation (A.2) is independent of the rest of the model and the distribution of $\tilde{\phi}$ is independent of the rest of the model, as well as the data, $\tilde{Y}_T$. Thus, I can generate $\tilde{\phi}$ conditional on $\tilde{F}_T$ according to the equation (A.2)

I rewrite the equation (A.5) in matrix form as follows:

$$\tilde{F}=\tilde{\phi}F_{-1}+V$$

And I employ a multivariate normal prior for $\tilde{\phi}$ given by

$$\tilde{\phi}\sim N(\underline{\alpha},\underline{A})_{I[S(\phi)]}$$

Where $\underline{\alpha}$ and $\underline{A}$ are known and $I[S(\phi)]$ is an indicator function used to denote that roots of $\phi(L)$ lie outside the unit circle. Combing the likelihood with the above prior distribution, I can derive the following posterior distribution, from which I can generate $\tilde{\phi}$:

$$\tilde{\phi} \sim N(\bar{\alpha}, \bar{A})_{I[S(\phi)]}$$

Where

$$\bar{\alpha} = (\underline{A}^{-1} + F_{-1}^{'}F_{-1})^{-1}(\underline{A}^{-1} + F_{-1}^{'}F)$$

$$\bar{A} = (\underline{A}^{-1} + F_{-1}^{'}F_{-1})^{-1}.$$

Step3: Generate $\tilde{\psi}_i$, b_i, σ_i^2, conditional on the dynamic factor $\tilde{F}_T$ and the data ($\tilde{Y}_T$), i= 1, 2, …, N

Conditional on $\tilde{F}_T$, equations (A.1) and (A.2) results in the regression model, each with auto-correlated disturbance. Therefore, I can employ normal priors for b_i and $\tilde{\psi}_i$, and an inverted Gamma distribution for σ_i^2 in the following way:

Priors:

$$b_i | \tilde{\psi}_{\mathrm{i}}, \sigma_i^2 \sim N(\underline{\alpha}_i, \underline{A}_i), \quad i = 1, 2, ..., N \tag{A.7}$$

$$\tilde{\psi}_{\mathrm{i}} | \mathrm{b}_{\mathrm{i}}, \sigma_i^2 \sim N(\underline{\alpha}_i^*, \underline{A}_i^*)_{I[S(\psi)]}, \quad i = 1, 2, ..., N \tag{A.8}$$

$$\sigma_i^2 | b_i, \tilde{\psi}_{\mathrm{i}} \sim IG(\frac{v_i}{2}, \frac{f_i}{2}), \quad i = 1, 2, ..., N \tag{A.9}$$

Where $\underline{\alpha}_i, \underline{A}_i, \underline{\alpha}_i^*, \underline{A}_i^*, v_i$ and $f_i, \quad i = 1, 2, ..., N$ are known.

3.1 Generate b_i, conditional on $\tilde{\psi}_i$, σ_i^2, $\tilde{F}_T$ and $\tilde{Y}_T$

By multiplying both sides of each of equations (2.1) by $\psi_i(L) = 1 - \psi_{i,1}, \quad i = 1, 2..., N$, I can have the following equations:

$$y_{i,t}^* = b_i^{world} f_t^{world*} + b_i^{region} f_{r,t}^{region*} + u_{i,t}, \quad u_{i,t} \sim \text{i.i.d.} N(o, \sigma_i^2), \text{ i=1,...,N} \tag{A.10}$$

Where

$y^*_{i,t} = y_{i,t} - \psi_{i,1} y_{i,t-1}$, $f_t^{world*} = f_t^{world} - \psi_{i,1} f_{t-1}^{world}$, $f_{r,t}^{region*} = f_{r,t}^{region} - \psi_{i,1} f_{r,t-1}^{region}$, and $\varepsilon_{i,t} = \psi_{i,1}\varepsilon_{i,t-1} + u_{i,t}$

If I stack all the factors together in matrix notation, I can have

$$\tilde{y}^*_{i,T} = b_i^{world}\tilde{f}_T^{world*} + b_i^{region}\tilde{f}_{r,T}^{region*} + U_i = b_i\tilde{F}_T^* + U_i,$$

$$\text{where } \mathrm{U}_i \sim \text{i.i.d.} N(o, \sigma_i^2 I_{T-1}),\ \text{i=1,...,N}$$

Combining with the likelihood with prior distribution in (A.7), I can derive the following posterior distribution, from which I can generate the parameters $\mathrm{b_i}$, i=1,...,N ,

Posterior:

$$b_i | \tilde{\psi}_i, \sigma_i^2, \tilde{F}_T, \tilde{Y}_T \sim N(\bar{\alpha}_i, \bar{A}_i), \quad i = 1, 2, ..., N$$

Where

$$\bar{\alpha}_i = (\underline{A}_i^{-1} + \sigma_i^{-2}\tilde{F}_T^{*'}\tilde{F}_T^{*})^{-1}(\underline{A}_i^{-1}\underline{\alpha}_i + \sigma_i^{-2}\tilde{F}_T^{*'}\tilde{Y}_T^{*}),$$
$$\bar{A}_i^{-1} = (\underline{A}_i^{-1} + \sigma_i^{-2}\tilde{F}_T^{*'}\tilde{F}_T^{*})^{-1},$$

3.2 Generate $\tilde{\psi}_i$, conditional on b_i, σ_i^2, $\tilde{F}_T$ and $\tilde{Y}_T$

To derive a posterior distribution of $\tilde{\psi}_i$, I can turn to equation (A.3):

$$\varepsilon_{i,t} = \psi_{i,1}\varepsilon_{i,t-1} + u_{i,t},\ u_{i,t} \sim i.i.d.N(o, \sigma_i^2),\ \text{i=1,...,N} \tag{A.11}$$

Where $\varepsilon_{i,t} = y_{i,t} - b_i^{world} f_t^{world} - b_i^{region} f_{r,t}^{region} = y_{i,t} - b_i f_t$ for i=1,...,N.

If I stack all the factors together in matrix notation, I can have

$$\tilde{\varepsilon}_{i,T} = E_i\tilde{\psi}_i + U_i,\ \mathrm{U}_i \sim i.i.d.N(o, \sigma_i^2 I_{T-1}),\ \text{i=1,...,N}$$

Combining with the likelihood with prior distribution in (A.8), I can derive the following posterior distribution, from which I can generate the parameters $\tilde{\psi}_i$, i=1,...,N ,

Posterior:

$$\tilde{\psi}_{\mathrm{i}}|\tilde{b}_i, \sigma_i^2, \tilde{F}_T, \tilde{Y}_T \sim N(\bar{\alpha}_i^*, \bar{A}_i^*)_{I[S(\psi)]}, \quad i = 1, 2, ..., N$$

Where

$$\begin{aligned}\bar{\alpha}_i^* &= (\underline{A}_i^{*-1} + \sigma_i^{-2} E_i^{*'} E_i^*)^{-1} (\underline{A}_i^{*-1} \underline{\alpha}_i^* + \sigma_i^{-2} E_i^{*'} \tilde{\varepsilon}_{i,T}),\\ \bar{A}_i^* &= (\underline{A}_i^{*-1} + \sigma_i^{-2} E_i^{*'} E_i^*)^{-1},\end{aligned}$$

3.3 Generate σ_i^2 conditional on b_i , $\tilde{\psi}_i$, $\tilde{F}_T$ and $\tilde{Y}_T$

Now, given b_i and ψ_i, I focus on (A.10) to get the likelihood of σ_i^2. Combining the likelihood with the prior distribution in (A.10), the posterior distribution from which σ_i^2 can be drawn is given as the following:

Posterior:

$$\sigma_i^2|\tilde{b}_i, \tilde{\psi}_{\mathrm{i}}, \tilde{F}_T, \tilde{Y}_T \sim IG(\frac{v_i + T - 1}{2}, \frac{f_i + (\tilde{\varepsilon}_{i,T} - E_i^* \tilde{\psi}_{\mathrm{i}})^{'} (\tilde{\varepsilon}_{i,T} - E_i^* \tilde{\psi}_{\mathrm{i}})}{2}), \quad i = 1, 2, ..., N$$

These steps are iterated S times, of which the first S_1 draws are discarded as a burning-in replications to remove the effects of initial values.

A2: Procedures for Time-varying VAR Model

In time-varying VAR Model, I need to estimate a number of parameters, including coefficients B^t and A^t, time-varying variance-covariance matrix Σ^t, and the hyper-parameters of matrix V. In this study, I employ the MCMC algorithm to construct the estimation of the parameters. The Prior distributions are assigned to the hyper-parameters in the model and then are combined with the information contained in the data (via the form of likelihood function). Together with a set of initial conditions, joint posterior distribution of the parameters can be estimated through Bayesian methods. Marginal posterior distributions are then obtained by integrating out other parameters from the joint posterior distribution.

Through the procedure of MCMC method, I can implement the analysis of the joint posterior distribution from Bayesian reference. It includes the following main steps:

Step 1: Priors Choosing

As suggested by Nakajima, et al (2011), I need to carefully choose the priors because the time-varying VAR (i.e., TV-VAR) model has many state variables for specification and their process is modeled as a non-stationary random walk process. In the TV-VAR model, flexible state variables can capture the changes of underlying financial shock because it allows time variation in each parameter in the model. Following Primiceri (2005), to avoid the implausible behaviors of time-varying parameters, I need tight prior for the covariance-matrix of the disturbance in the random walk process, which is helpful for the identification in the model.

In this study, the time-varying coefficient (B) needs a tighter prior than the simultaneous relations (A) and the variance (h) of the financial shock for the variance of the disturbance in their time-varying process. The financial shock may unexpectedly hits the financial system and the variance might widely fluctuate over time. In the following estimation procedures, I set a slightly tighter prior for Σ_B and a rather diffuse prior for Σ_A and Σ_h. In addition, since the time-varying parameters are random walks, I need to set the prior of the normal distribution for the initial state of each time-varying parameter. As suggested by Primiceri (2005), the estimates from the time-invariant VAR model during pre-sample period are used as the priors in the model.

Step 2: Simulation method to generate the posterior distribution

The model is estimated by simulating the distribution of the parameters, given the real data. In this section, I employ the MCMC algorithm to generate a sample from the joint posterior of B_t, A_t, Σ_t, and V. The Gibbs sampling is used in order to exploit the blocking structure of the unknowns. In this study, Gibbs sampling is carried out in four steps, drawing in turn the time varying coefficients (B_t), simultaneous relations (A_t), volatilities (Σ_t) and the hyper-parameters (V), conditional on the observed real data (y_t) and the remaining parameters. Given the real data y, I draw sample from the posterior distribution by using the MCMC method. The main MCMC algorithm for this study is as follows.

Since the state space form given is linear and Gaussian, the conditional posterior of B_t is a product of Gaussian densities and B_t can be drawn using a standard simulation smoother (Carter and Kohn, 1994) conditional on A_t and Σ_t. Similarly, the posterior of A_t conditional on B_t and Σ_t is also a product of normal distributions. Hence, A_t can also be drawn in the same way. Drawing Σ_t is more involved and relies mostly on the method presented in Kim et al. (1998). It needs to transform a nonlinear and non-Gaussian state space form to a linear and approximately Gaussian one, which again, allows the use of simulation smoothers. Simulating the conditional posterior of V is standard, since it is the product of independent inverse-Wishart distributions. Simply taken together, the algorithm of MCMC is summarized as follows:

1): Initialize B, A, and V;
2): Sample B conditional on A, Σ, V and real data y;
3): Sample A conditional on B, Σ, V and real data y;
4) Sample V conditional on B, A, Σ, and real data y;
5) Sample Σ conditional on B, A, V and real data y.

As discussion on Gibbs sampling above, the iteration will go to step 2 again after all the steps are conducted. Steps 2 to 4 are conducted with the simulation smoother, and step 5 requires the multi-move sampler for the stochastic volatility. For further details of the Gibbs Sampling for state space model, see the book of Kim and Nelson (1999) as reference.

Tables

Table 2.1: Regional Definition and Classification

Oceanian Developed	Asian Developed	Asian Emerging	European Developed	North American Developed	South America Emerging
Australia New Zealand	Hong Kong Japan Singapore	Indonesia Malaysia Philippines South Korea Taiwan Thailand	Austria Belgium Denmark France Finland Germany Greece Ireland Italy Netherland Norway Portugal Spain Sweden Switzerland United Kingdom	Canada USA	Argentina Brazil Chile Mexico Peru

Notes: MCSI Criteria are employed to classify different markets into the developed and emerging markets. See (http://www.msci.com/equity/coverage_matrix.pdf) for more information about the MSCI classifications. In this study, based on geographical closeness, market developments and interactions, international stock markets in this study are classified into 6 different regions.

The details of national stock market indices are as follows: *The Standard and Poor's 500 Composite Index for USA; the S&P/TSX Composite Index for Canada; the All Ordinaries index for Australia; the NZSE50 index for New Zealand; the Hang Seng Price Index for Hong Kong; the Nikkei225 Index for Japan; the Korean Stock Exchange composite Index for Korea; the Singapore Straits Times Price Index for Singapore; the Taiwan Stock Exchange weighted-price Index for Taiwan; the Bangkok S.E.T. Price Index for Thailand; the FTSE Bursa Malaysia Index Index for Malaysia; the Mseusinf Index for Indonesia; the Philippine Stock Exchange Index (PSEI) for Philippine; the Austrian Traded Index (ATX) for Austria; the BEL20 index for Blgium; the OMX Copenhagen 20 (OMXC20) Index for Denmark; the OMX Helsinki 25 Index for Finland; the CAC40 Index for France; the DAX30 Index for German; the ISEQ 20 Index for Ireland, the PSI-20 Index for Portugal; the FTSE Italia MIB Storico Index for Italy; the AEX Index for Netherland; the OBX Index for Norway; the IBEX Index for Spain; the Athex Composite Share Price Index for Greece; the Swiss Market Index (SMI) for Switzerland; the FTSE 100 Index for United Kingdom; the Bovespa Index for Brazil; the Mexican Bolsa IPC Index for Mexico; the Merval Index for Argentina; the General Stock Price Index (IGPA) for Chile; the Lima SE General (IGBL) Index for Peru*.

Table 2.2: First-order Auto-regression Coefficients

Type of Factors	AR(1) Coefficient
World	0.371
Oceania	0.243
Asia (Developed)	0.289
Asia (Emerging)	0.437
Europe	0.310
North America	0.210
South America	0.234

Notes: The table presents AR(1) coefficients of the common world and 6 different regional factors, respectively. The coefficients can be used to measure the adjustment speed to the global or regional shocks for the markets in the world or within its region.

Table 2.3: Factors Coefficients and Country Factors AR(1) Coefficients

Market	World coefficient	Regional coefficient	Country factor AR(1)
Australia	2.372	1.558	0.163
New Zealand	2.827	0.850	0.125
Hong Kong	4.331	3.334	0.237
Japan	3.501	0.250	0.285
Singapore	3.840	3.199	0.231
Indonesia	3.650	2.508	0.190
Korea	4.473	3.344	0.117
Malaysia	2.625	3.571	0.105
Philippines	3.970	3.719	0.119
Taiwan	3.268	1.729	0.327
Thailand	3.768	4.711	0.165
UK	3.014	0.903	0.085
Australia	4.456	-0.436	0.213
Belgium	3.652	1.011	0.209
Denmark	3.749	1.035	0.100
Finland	4.299	2.376	0.259
France	3.673	2.148	0.110
Germany	3.963	2.387	0.264
Greece	4.456	1.268	0.259
Ireland	4.226	0.693	0.287
Italy	3.853	2.255	0.115
Netherlands	4.503	1.790	0.157
Norway	4.824	0.495	0.160
Portugal	3.350	1.463	0.303
Spain	3.630	1.578	0.065
Sweden	3.975	1.840	0.164
Switzerland	3.210	1.466	0.231
Canada	3.366	1.077	0.212
USA	3.221	0.924	0.195
Argentina	4.967	4.904	0.184
Brazil	5.837	2.667	0.726
Mexico	4.411	2.450	0.124
Chile	2.478	1.335	0.188
Peru	4.252	2.297	0.346

Notes: The 2nd and 3rd columns present the factor loading of common world and regional factor for different markets in the world, respectively. The 4th column presents the AR(1) coefficients of different Country-specific factors.

Table 2.4.1: Variance Decompositions for Stock Market Returns

Market	World %	Region %	Country %
Australia	84.231	7.028	8.741
New Zealand	65.567	25.599	8.835
Hong Kong	60.127	33.522	6.351
Japan	49.053	0.235	50.712
Singapore	58.211	38.004	3.7853
Indonesia	41.067	24.463	34.469
Korea	28.404	14.291	57.305
Malaysia	20.064	39.592	40.344
Philippines	35.829	33.507	30.664
Taiwan	27.622	8.238	64.141
Thailand	25.420	42.358	32.221
UK	74.175	6.350	19.475
Austria	71.402	0.653	27.944
Belgium	67.545	4.939	27.516
Denmark	66.185	4.813	29.003
Finland	39.496	11.521	48.983
France	69.243	22.605	8.152
Germany	65.110	22.539	12.350
Greece	40.955	3.164	55.881
Ireland	67.782	1.739	30.479
Italy	54.997	17.970	27.033
Netherlands	80.097	12.081	7.822
Norway	75.835	0.761	23.404
Portugal	53.833	9.801	36.366
Spain	64.871	11.698	23.431
Sweden	63.123	12.907	23.970
Switzerland	61.926	12.333	25.741
Canada	79.552	7.351	13.098
USA	83.699	6.211	10.090
Argentina	36.959	32.880	30.161
Brazil	26.052	4.962	68.987
Mexico	49.772	13.552	36.676
Chile	33.580	8.899	57.522
Peru	35.625	9.491	54.884

Table 2.4.2: Variance Decompositions for Developed and Emerging Market Returns

Panel 1			
Regional Markets Average	World %	Region %	Country %
Oceania Average	74.899	16.313	8.788
Asia (Developed) Average	55.797	23.920	20.283
Asia (Emerging) Average	29.734	27.075	43.191
Europe Average	63.536	9.742	26.722
North America Average	81.625	6.781	11.594
South America Average	36.397	13.957	49.646
Panel 2			
Developed Markets Average	65.088	11.905	23.007
Emerging Markets Average	32.763	21.112	46.125

Notes: The 2nd, 3rd and 4th columns in Tables 2.4.1 and 2.4.2 present the variance shares of different markets for the world, regional and country-specific factors respectively. Table 2.4.2 present the results of the average of variance shares of world factor, regional factor and country-specific factor for the stock markets within the same region, respectively. The average of the variance shares for developed markets and emerging markets are also presented in Panel 2 of Table 2.4.2.

Table 2.5: Bilateral Correlation Coefficients

Bilateral markets	Simple	Bayesian	Bilateral markets	Simple	Bayesian
AUS-NZL	0.740	0.908	FRA-AUT	0.674	0.665
USA-CAN	0.813	0.884	FRA-BEL	0.792	0.790
HKG-JPN	0.499	0.571	FRA-DNK	0.759	0.781
HKG-SIN	0.780	0.949	FRA-FIN	0.703	0.684
JPN-SIN	0.530	0.564	FRA-DEU	0.906	0.897
KOR-IDN	0.558	0.529	FRA-GRC	0.649	0.617
KOR-MYS	0.494	0.477	FRA-IRL	0.737	0.748
KOR-PHL	0.484	0.538	FRA-ITA	0.819	0.819
KOR-TWN	0.489	0.389	FRA-NLD	0.905	0.910
KOR-THA	0.600	0.515	FRA-NOR	0.764	0.766
IDN-MYS	0.637	0.598	FRA-PRT	0.776	0.759
IDN-PHL	0.670	0.670	FRA-ESP	0.842	0.833
IDN-TWN	0.431	0.479	FRA-SWE	0.837	0.832
IDN-THA	0.644	0.645	FRA-CHE	0.808	0.822
MYS-PHL	0.655	0.632	FRA-GBR	0.853	0.836
MYS-TWN	0.398	0.416	DEU-AUT	0.658	0.643
MYS-THA	0.615	0.635	DEU-BEL	0.755	0.769
PHL-TWN	0.511	0.481	DEU-DNK	0.764	0.761
PHL-THA	0.689	0.679	DEU-FIN	0.666	0.668
TWN-THA	0.463	0.452	DEU-GRC	0.590	0.601
ARG-BRA	0.462	0.438	DEU-IRL	0.714	0.727
ARG-CHIL	0.693	0.640	DEU-ITA	0.797	0.800
ARG-MEX	0.499	0.523	DEU-NLD	0.898	0.887
ARG-PER	0.588	0.540	DEU-NOR	0.752	0.744
BRA-CHL	0.468	0.442	DEU-PRT	0.755	0.741
BRA-MEX	0.497	0.362	DEU-ESP	0.804	0.812
BRA-PER	0.524	0.373	DEU-SWE	0.830	0.812
CHL-MEX	0.496	0.519	DEU-CHE	0.813	0.802
CHL-PER	0.508	0.534	DEU-GBR	0.796	0.815
MEX-PER	0.570	0.438	GBR-ITA	0.720	0.746
GBR-AUT	0.690	0.707	GBR-NLD	0.868	0.858
GBR-BEL	0.777	0.764	GBR-NOR	0.747	0.772
GBR-DNK	0.733	0.756	GBR-PRT	0.686	0.711
GBR-FIN	0.626	0.627	GBR-ESP	0.766	0.780
GBR-GRC	0.581	0.596	GBR-SWE	0.755	0.775
GBR-IRL	0.759	0.742	GBR-CHE	0.808	0.766

Notes: Columns 2^{nd} and 5^{th}, and 3^{rd} and 6^{th} respectively present the simple pair-wise correlations coefficients and the bilateral correlation coefficients on the basis of the Bayesian dynamic factor model within each region.

Table 3.1: Date when Infected Markets were Impacted

Infected markets were impacted during the crisis	
Country	Date
Thailand	02-Jul-1997
Philippines	11-Jul-1997
Malaysia	14-Jul-1997
Indonesia	14-Aug-1997
Singapore	28-Aug-1997
Taiwan	17-Oct-1997
Hong Kong	17-Oct-1997
South Korea	17-Nov-1997
Japan	19-Dec-1997

Notes: Table 3.1 presents the dates for main Asian markets when the Infected Markets were impacted during the financial crisis.

Table 3.2: Summary statistics for the Realized Volatility (RV) Indices

		Mean	Mdn	Max	Min	Std. Dev.	Skew	Kurtosis	Jarque-Bera
Overall period Jan/95 - Dec/99 (261 obs.)	TH	20.771	11.935	255.016	0.259	29.320	3.902	23.528	5245.089
	PH	13.930	6.170	142.700	0.221	20.788	3.223	15.692	2203.753
	MA	24.035	6.055	1127.462	0.000	86.612	9.658	111.492	132062.300
	IN	19.358	5.176	211.662	0.000	34.086	2.962	12.519	1366.842
	SG	11.486	4.059	196.936	0.159	23.553	5.280	36.665	13537.780
	TW	11.198	6.513	82.160	0.000	12.755	2.518	11.167	1001.225
	HK	18.663	7.822	570.947	0.540	44.866	8.469	94.312	93795.650
	SK	24.655	10.754	169.228	0.095	34.194	2.503	9.248	697.153
	JP	10.090	6.388	110.049	0.002	12.157	3.774	24.263	5536.150
Sub-period Jan/95 - Jun/97 (130 obs.)	TH	9.829	5.868	54.624	0.259	10.276	2.028	7.513	199.486
	PH	6.311	3.773	41.834	0.221	7.022	2.340	9.853	373.039
	MA	4.894	2.705	30.716	0.000	5.680	2.321	8.710	293.265
	IN	3.843	2.761	34.060	0.000	5.001	3.853	21.062	2088.651
	SG	3.219	2.210	43.708	0.209	4.704	5.901	46.759	11126.640
	TW	8.999	5.280	48.721	0.106	9.821	1.955	6.924	166.209
	HK	6.674	4.116	77.779	0.540	8.887	4.744	34.100	5726.792
	SK	7.365	5.534	37.483	0.155	6.408	1.942	7.556	194.154
	JP	7.790	4.912	48.710	0.002	8.262	2.406	9.665	366.068
Sub-period Jul/97-Dec/99 (131 obs.)	TH	31.629	19.105	255.016	1.504	37.095	3.004	14.339	898.910
	PH	21.492	9.978	142.700	0.589	26.451	2.292	8.846	301.221
	MA	43.030	17.584	1127.462	0.658	119.337	6.920	57.531	17276.330
	IN	34.753	16.530	211.662	0.000	42.654	1.951	6.594	153.606
	SG	19.689	10.379	196.936	0.159	30.844	3.908	20.404	1986.789
	TW	13.381	8.543	82.160	0.000	14.834	2.396	9.667	367.944
	HK	30.561	15.251	570.947	2.482	60.507	6.325	52.000	13978.780
	SK	41.813	27.477	169.228	0.095	41.257	1.628	4.919	77.927
	JP	12.371	8.012	110.049	0.234	14.741	3.501	19.479	1749.856

Notes: Observations for all series in the whole sample period are 261. The observations for the two different sub-periods are 260, and 261, respectively. Here I just simply choose the July, 2nd, 1997, as the breakpoint of the sample period.

Table 3.3.1: Simple Correlation of the Realized Volatility

3.3.1A: Constant correlation coefficients before crisis

	TH	PH	MA	IN	SG	TW	HK	SK	JP
TH	1.000								
PH	0.184	1.000							
MA	0.110	0.410	1.000						
IN	0.175	0.340	0.461	1.000					
SG	0.216	0.265	0.621	0.421	1.000				
TW	-0.029	-0.035	0.030	-0.011	0.069	1.000			
HK	0.195	0.252	0.534	0.458	0.581	0.037	1.000		
SK	0.222	-0.003	0.051	0.060	0.223	-0.01	0.091	1.000	
JP	0.080	0.030	0.211	-0.073	0.244	0.072	0.118	0.396	1.000

3.3.1B: Constant correlation coefficients after crisis

	TH	PH	MA	IN	SG	TW	HK	SK	JP
TH	1.000								
PH	0.443	1.000							
MA	0.252	0.197	1.000						
IN	0.383	0.613	0.204	1.000					
SG	0.543	0.615	0.338	0.674	1.000				
TW	0.087	0.050	0.245	0.128	0.231	1.000			
HK	0.294	0.387	0.252	0.500	0.572	0.442	1.000		
SK	0.204	0.177	0.085	0.272	0.323	0.221	0.360	1.000	
JP	0.158	0.132	0.314	0.266	0.215	0.127	0.337	0.334	1.000

Notes*: TH, PH, MA, IN, SG, TW, HK, SK, JP* represent the realized volatility of Thailand, Philippines, Malaysia, Indonesia, Singapore, Taiwan, Hong Kong, South Korea, and Japan markets, respectively. The tables present the pair-wise correlation coefficients between these stock markets before and after crisis, respectively.

Table 3.3.2: Correlation of the Realized Volatility (After Adjusted)

	Correlation before crisis	Correlation after crisis	Z-statistics
TH-PH	0.184444	0.442556	-4.6031***
TH-MA	0.109975	0.252200	-2.3482***
TH-IN	0.175423	0.383092	-3.6086***
TH-SG	0.215895	0.543401	-6.2096***
TH-TW	-0.029230	0.087392	-1.8623**
TH-HK	0.195452	0.294286	-1.6775**
TH-SK	0.222093	*0.204276*	0.29749
TH-JP	0.080334	0.157847	-1.2538
PH-MA	0.410366	*0.197029*	3.76778
PH-IN	0.340258	0.612926	-5.7249***
PH-SG	0.265496	0.614813	-7.0860***
PH-TW	-0.03573	0.049716	-1.3627*
PH-HK	0.252325	0.387182	-2.4000***
PH-SK	-0.00383	0.177296	-2.9169***
PH-JP	0.030253	0.132206	-1.6371**
MA-IN	0.453640	*0.201619*	4.5397
MA-SG	0.613918	*0.336949*	5.8096
MA-TW	0.025529	0.242600	-3.5380***
MA-HK	0.536339	*0.250429*	5.46845
MA-SK	0.038741	0.081198	-0.6792
MA-JP	0.203224	0.312806	-1.8735**
IN-SG	0.470856	0.668489	-4.7255***
IN-TW	-0.008796	0.116998	-2.0112***
IN-HK	0.407939	0.493718	-1.7166***
IN-SK	0.026544	0.249192	-3.6297***
IN-JP	-0.018500	0.258179	-4.4998***
SG-TW	0.073236	0.221629	-2.4188***
SG-HK	0.556545	0.567279	-0.2496
SG-SK	0.202875	0.305124	-1.7414**
SG-JP	0.269926	*0.205280*	1.0908
TW-HK	0.173883	0.433124	-4.5589***
TW-SK	0.044545	0.209059	-2.6526***
TW-JP	0.071795	0.121511	-0.7944
HK-SK	0.139266	0.355523	-3.6649***
HK-JP	0.112397	0.332136	-3.6772***
SK-JP	0.410849	*0.293443*	2.1163

Notes: I choose the country as the crises source according to the order of date in which the infected markets were impacted during the crises. The null hypothesis is no increase in correlation. The 1%, 5%, and 10% critical values for a one-sided test of the null are -2.32, -1.64, and -1.28, respectively. And ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.4: Constant Correlation of the Realized Volatility (in VAR Model)

3.4A: Constant correlation coefficients before crisis

	TH	PH	MA	IN	SG	TW	HK	SK	JP
TH	1.000								
PH	0.146	1.000							
MA	0.180	0.271	1.000						
IN	0.168	0.367	0.529	1.000					
SG	0.227	0.190	0.622	0.440	1.000				
TW	0.084	-0.007	0.102	-0.003	0.079	1.000			
HK	0.245	0.210	0.526	0.493	0.589	0.092	1.000		
SK	0.168	-0.006	0.114	0.097	0.281	0.048	0.109	1.000	
JP	0.102	0.065	0.175	-0.055	0.269	0.108	0.139	0.380	1.000

3.4B: Constant correlation coefficients after crisis

	TH	PH	MA	IN	SG	TW	HK	SK	JP
TH	1.000								
PH	0.360	1.000							
MA	0.297	0.015	1.000						
IN	0.337	0.546	0.133	1.000					
SG	0.525	0.549	0.342	0.632	1.000				
TW	0.113	0.005	0.254	0.133	0.216	1.000			
HK	0.284	0.318	0.256	0.513	0.555	0.398	1.000		
SK	0.210	0.142	0.086	0.2356	0.277	0.193	0.278	1.000	
JP	0.174	0.043	0.305	0.241	0.166	0.116	0.322	0.286	1.000

Notes*: TH, PH, MA, IN, SG, TW, HK, SK, JP* represent the realized volatility of Thailand, Philippines, Malaysia, Indonesia, Singapore, Taiwan, Hong Kong, South Korea, and Japan markets, respectively. The tables present the correlation coefficients between these stock markets before and after crisis, respectively, which is based on the constant VAR model.

Table 3.5: Mean-DCC of the Market Volatility in GARCH Model

	TH	PH	MA	IN	SG	TW	HK	SK	JP
Panel A: Thailand (Before Crisis & After Crisis)									
Before	NA	0.4575	0.3703	0.4738	0.4818	0.4013	0.4989	0.4420	0.4558
After	NA	0.4724	0.4518	0.5020	0.5348	0.4784	0.5726	0.5087	0.5159
Panel B: Hong Kong (Before Crisis & After Crisis)									
Before	0.4989	0.3315	0.3996	0.4067	0.7566	0.3902	NA	0.3624	0.3412
After	0.5726	0.4622	0.4281	0.4067	0.7049	0.5969	NA	0.5737	0.5137

The tables present the average of the correlation coefficients between Hong Kong (or Thailand) and other Asian markets during two different periods of before and after crisis, respectively, which is based on the DCC-GARCH model.

Table 3.6: Mean-DCC of the Market Volatility in Time-varying VAR Model

	TH	PH	MA	IN	SG	TW	HK	SK	JP
Panel A: Thailand (Before Crisis & After Crisis)									
Before	NA	0.0310	-0.0627	-0.0437	-0.0348	-0.0295	0.0186	-0.0602	0.0624
After	NA	0.0826	-0.1304	-0.0421	-0.0156	-0.0044	0.0417	-0.0419	0.0723
Panel B: Hong Kong (Before Crisis & After Crisis)									
Before	0.0186	0.0671	0.0858	-0.0634	0.0581	-0.0601	NA	0.0463	0.0167
After	0.0417	0.0685	0.0553	-0.0634	0.0873	-0.0354	NA	0.0805	0.1034

The tables present the average of the correlation coefficients between Hong Kong (or Thailand) and other Asian markets during two different periods of before and after crisis, respectively, which is based on the Time-varying VAR model.

Table 3.7: Decomposition of Variance for Asian Markets

Panel A: With Thailand

Before crisis				After crisis			
Variance Decomposition of PH:				Variance Decomposition of PH:			
Period	S.E.	TH	PH	Period	S.E.	TH	PH
1	6.312198	2.143637	97.85636	1	24.46950	14.48696	85.51304
5	7.102561	1.926554	98.07345	5	27.11024	14.55126	85.44874
10	7.103918	1.925823	98.07418	10	27.34523	14.34666	85.65334
Variance Decomposition of MA:				Variance Decomposition of MA:			
Period	S.E.	TH	MA	Period	S.E.	TH	MA
1	5.250517	3.244217	96.75578	1	112.3139	10.11196	89.88804
5	5.753640	2.849765	97.15024	5	120.5768	8.958227	91.04177
10	5.754757	2.858584	97.14142	10	120.5813	8.957734	91.04227
Variance Decomposition of IN:				Variance Decomposition of IN:			
Period	S.E.	TH	IN	Period	S.E.	TH	IN
1	5.039869	2.807820	97.19218	1	39.53424	13.88279	86.11721
5	5.057964	3.334184	96.66582	5	43.70854	16.24828	83.75172
10	5.057980	3.334689	96.66531	10	43.77498	16.24439	83.75561
Variance Decomposition of SG:				Variance Decomposition of SG:			
Period	S.E.	TH	SG	Period	S.E.	TH	SG
1	4.694438	5.171959	94.82804	1	27.77865	27.22547	72.77453
5	4.757336	5.348546	94.65145	5	31.58768	21.34209	78.65791
10	4.757339	5.348644	94.65136	10	31.81265	21.21824	78.78176
Variance Decomposition of TW:				Variance Decomposition of TW:			
Period	S.E.	TH	TW	Period	S.E.	TH	TW
1	9.449428	0.709344	99.29066	1	14.55431	1.736501	98.26350
5	9.999118	6.342821	93.65718	5	14.95983	2.749996	97.25000
10	10.00148	6.379931	93.62007	10	14.95984	2.750091	97.24991
Variance Decomposition of HK:				Variance Decomposition of HK:			
Period	S.E.	TH	HK	Period	S.E.	TH	HK
1	8.636631	6.005992	93.99401	1	56.60221	9.424987	90.57501
5	8.779696	5.971904	94.02810	5	61.09828	8.216777	91.78322
10	8.779750	5.973057	94.02694	10	61.09935	8.216713	91.78329
Variance Decomposition of SK:				Variance Decomposition of SK:			
Period	S.E.	TH	SK	Period	S.E.	TH	SK
1	6.133715	2.826952	97.17305	1	38.16984	5.404547	94.59545
5	6.491022	5.652022	94.34798	5	41.58197	4.600304	95.39970
10	6.491371	5.660938	94.33906	10	41.58346	4.600592	95.39941
Variance Decomposition of JP:				Variance Decomposition of JP:			
Period	S.E.	TH	JP	Period	S.E.	TH	JP
1	8.098045	0.893732	99.10627	1	13.42224	2.206768	97.79323
5	8.406994	2.082804	97.91720	5	14.78580	2.951484	97.04852
10	8.409489	2.106086	97.89391	10	15.24013	3.008584	96.99142

Panel B: With Hong Kong

Before crisis				After crisis			
Variance Decomposition of TH:				Variance Decomposition of TH:			
Period	S.E.	HK	TH	Period	S.E.	HK	TH
1	9.579146	6.005992	93.99401	1	34.26359	9.424987	90.57501
5	10.52602	6.156304	93.84370	5	35.56438	12.28797	87.71203
10	10.52677	6.156490	93.84351	10	35.56474	12.28948	87.71052
Variance Decomposition of PH:				Variance Decomposition of PH:			
Period	S.E.	HK	PH	Period	S.E.	HK	PH
1	6.301113	4.394456	95.60554	1	24.51465	13.20001	86.79999
5	7.102184	5.933481	94.06652	5	26.39565	14.56357	85.43643
10	7.103839	5.937234	94.06277	10	26.40337	14.57954	85.42046
Variance Decomposition of MA:				Variance Decomposition of MA:			
Period	S.E.	HK	MA	Period	S.E.	HK	MA
1	5.264450	27.65240	72.34760	1	109.5001	5.122043	94.87796
5	5.745552	27.72973	72.27027	5	123.2402	14.29812	85.70188
10	5.745859	27.72978	72.27022	10	123.5206	14.66847	85.33153
Variance Decomposition of IN:				Variance Decomposition of IN:			
Period	S.E.	HK	IN	Period	S.E.	HK	IN
1	5.042315	24.31467	75.68533	1	40.98319	26.21204	73.78796
5	5.055345	24.22983	75.77017	5	43.05786	27.58556	72.41444
10	5.055345	24.22983	75.77017	10	43.05816	27.58653	72.41347
Variance Decomposition of SG:				Variance Decomposition of SG:			
Period	S.E.	HK	SG	Period	S.E.	HK	SG
1	4.589848	34.64386	65.35614	1	29.21603	30.71278	69.28722
5	4.749412	38.92833	61.07167	5	31.16785	33.03064	66.96936
10	4.749412	38.92833	61.07167	10	31.16849	33.03304	66.96696
Variance Decomposition of TW:				Variance Decomposition of TW:			
Period	S.E.	HK	TW	Period	S.E.	HK	TW
1	9.615264	0.844675	99.15532	1	14.63995	15.81324	84.18676
5	9.922613	1.654798	98.34520	5	14.98338	17.28117	82.71883
10	9.922636	1.654941	98.34506	10	14.98346	17.28164	82.71836
Variance Decomposition of SK:				Variance Decomposition of SK:			
Period	S.E.	HK	SK	Period	S.E.	HK	SK
1	6.167931	1.178649	98.82135	1	33.90289	9.982104	90.01790
5	6.481702	1.105054	98.89495	5	38.74114	25.89398	74.10602
10	6.481729	1.105045	98.89495	10	42.67619	34.56104	65.43896
Variance Decomposition of JP:				Variance Decomposition of JP:			
Period	S.E.	HK	JP	Period	S.E.	HK	JP
1	8.159530	1.919904	98.08010	1	11.29481	10.52125	89.47875
5	8.333654	2.226628	97.77337	5	14.75860	40.88310	59.11690
10	8.333654	2.226632	97.77337	10	15.28951	43.43482	56.56518

Table 4.1: Monthly Data Descriptions (1995.01-2009.12)

Symbol	Definition	Source of Data	Transformation
returns	Price index in local currency	DataStream;	Month-on-Month
IP	Industrial production, seasonally adjusted	GEM	Year-on-Year
Inflation	Price index, seasonally adjusted	GEM	Year-on-Year
Interest	Short-term interest rates	IFS	Interest

Notes:

1. IFS denotes International Financial Statistics from IMF; and GEM denotes Global Economic Monitor from World Bank database;
2. Stock market data: A few of them are obtained from Bloomberg data resources for the unavailability from the Datastream International;
3. Stock prices are the average price indices in all trading dates in each entire month t.
4. Stock market returns: I mainly focus on stock market real returns in this study. For being consistent with the measurement of the macroeconomic variables, stock market returns are multiplied by 12 to make them be annual data.
5. Short-term interest rates in a few countries are not available. Here I use the money market rates (or deposit rates) as the proxies.

Table 4.2: Summary Statistics for Real Returns

Country	Mean	Std. Dev.	Min	Max
Argentina	3.885	113.330	-406.605	407.601
Australia	3.341	42.161	-206.027	118.672
Austria	4.033	70.868	-476.575	193.089
Belgium	1.994	59.900	-362.942	138.898
Brazil	1.449	129.635	-834.768	279.074
Canada	4.939	52.7460	-302.582	133.060
Chile	2.808	52.984	-215.587	186.415
Denmark	6.373	61.321	-337.436	195.275
Finland	6.659	92.456	-305.569	311.494
France	3.012	58.719	-236.01	131.979
Germany	5.443	66.371	-263.698	154.387
Greece	1.945	91.720	-374.54	358.075
Hong Kong	5.267	80.789	-297.313	199.220
Indonesia	-1.484	95.430	-435.779	286.342
Ireland	0.494	69.504	-385.466	178.772
Italy	1.461	67.400	-275.584	200.391
Japan	-4.231	64.523	-348.772	167.912
Korea	-0.480	93.526	-305.826	258.479
Malaysia	-0.782	78.104	-302.466	298.148
Mexico	5.590	81.213	-291.208	181.685
Netherlands	1.612	67.989	-382.231	176.172
New Zealand	-1.563	40.364	-152.989	143.328
Norway	5.139	74.203	-435.682	188.011
Peru	10.767	94.014	-469.669	323.479
Philippines	-5.072	85.287	-312.238	290.087
Portugal	4.768	62.276	-267.479	157.875
Singapore	0.415	75.536	-317.297	258.075
Spain	6.594	60.598	-211.869	164.029
Sweden	6.787	67.238	-276.279	166.204
Switzerland	5.171	54.290	-190.546	179.035
Taiwan	-0.369	78.734	-247.557	239.448
Thailand	-7.513	98.999	-339.198	339.097
United Kingdom	1.080	46.021	-244.575	116.815
United States	3.443	49.340	-280.312	137.512

Notes: The sample period covered in this analysis is January 1995 to December 2009. Stock market real returns are obtained by subtracting inflation rates from nominal returns.

Table 4.4.3: Variance Share of Global Factor

Country	Industrial production	Inflation	Interest	Real returns	Nominal returns
Argentina	17.610	0.596	0.012	33.951	31.954
Australia	25.890	40.126	39.521	70.044	69.149
Austria	75.904	71.598	53.967	63.711	63.226
Belgium	79.168	67.694	57.116	71.675	71.221
Brazil	36.569	1.530	27.789	34.515	52.564
Canada	68.831	44.589	47.996	74.757	74.618
Chile	29.171	32.653	39.245	32.382	32.355
Denmark	35.584	32.359	60.991	72.355	72.121
Finland	86.260	36.847	58.201	51.182	50.661
France	86.949	67.924	76.426	87.016	86.729
Germany	86.251	62.103	50.296	83.678	83.449
Greece	44.991	17.902	55.301	45.587	45.389
Hong Kong	25.023	9.129	28.839	45.408	46.000
Indonesia	0.519	3.7016	3.785	37.901	38.302
Ireland	19.846	49.608	66.896	69.896	69.020
Italy	88.028	44.279	79.174	75.956	75.885
Japan	76.253	11.783	20.241	49.428	49.396
Korea	21.934	4.366	29.735	29.046	28.960
Malaysia	38.480	15.613	21.037	18.821	18.394
Mexico	26.868	0.656	44.500	46.137	48.476
Netherlands	46.883	11.129	31.658	90.815	90.679
New Zealand	35.794	42.326	40.244	46.564	45.956
Norway	6.168	10.024	12.986	75.590	75.610
Peru	25.349	4.104	27.204	33.008	33.650
Philippines	N/A	6.759	21.149	32.694	32.364
Portugal	28.664	41.428	52.421	66.954	66.720
Singapore	17.729	44.133	12.351	45.040	44.515
Spain	84.622	81.100	81.089	76.497	76.343
Sweden	83.688	48.963	76.354	76.051	75.834
Switzerland	58.212	76.189	37.353	73.289	72.900
Taiwan	34.884	35.243	N/A	32.345	32.393
Thailand	19.441	17.987	20.581	20.575	20.791
United Kingdom	86.974	42.746	42.855	81.240	80.913
United States	79.677	70.017	37.215	81.114	80.999
			91.76(Euro)		
Average	**47.825**	**33.741**	**41.046**	**56.624**	**56.986**

Notes: Variance share denotes the share of the variance of national series that are attributable to the global factors. Table presents the results for 5 different variables of the global factors, including for industrial production, inflation, interest rate, real returns, and nominal returns. The data of industrial production for Philippines and Interest rates for Taiwan are not available.

Table 4.4: Average of Variance Share of Global Factor

	Industrial Production	Inflation	Interest	Real returns	Nominal returns
Average of Total Countries	47.825	33.741	41.046	56.624	56.986
Average of Developed Countries	56.118	43.416	47.503	66.434	66.172

Notes: Table 4.4 presents the average of variance shares of the global factor for Industrial production, Inflation, Interest, Real returns, and Nominal returns, respectively, for pooled and developed countries.

Table 4.5: Pair-wise Correlation among Different Global Factors

	IP	Inflation	Interest	Real	Nominal
IP	1				
Inflation	0.466	1			
Interest	0.529	0.517	1		
Real	0.040	-0.311	-0.081	1	
Nominal	0.047	-0.298	-0.070	0.999	1

Notes: Pair-wise correlation coefficients among global macroeconomic factors (represented by industrial production, inflation, and interest rate) and stock market returns (real returns and nominal returns) are reported respectively.

Table 4.6: Results of VAR Analysis

REAL SECTION in VAR SYSTEM				
	IP	INFLATION	INTEREST	REAL
LAG_1	33.06408 (26.9395)	-37.374 (24.5978)	-25.3171 (85.0488)	0.284704 (0.08472)
LAG_2	25.40825 (44.9141)	37.28729 (57.1802)	89.83857 (219.819)	-0.17857 (0.08548)
LAG _3	-78.7686 (43.5939)	11.35692 (72.1319)	-143.547 (281.364)	0.006162 (0.08615)
LAG _4	58.75887 (43.7296)	-95.088 (72.9088)	76.48290 (264.439)	-0.03602 (0.08329)
LAG _5	-48.9108 (43.4560)	89.59079 (60.0407)	22.04031 (173.593)	0.079098 (0.08189)
LAG _6	23.39628 (25.3515)	-13.0332 (27.8854)	-22.0349 (52.8050)	-0.22964 (0.08133)

Notes: Table 4.6 presents the estimation results which are based on the VAR analysis, including the variables of the global factors of Industrial production, Inflation, Interest, and Real returns. The values of standard error are presented in parentheses.

Table 4.7: Variance Decomposition (Real Returns)

Variance Decomposition of REAL:				
Period	REAL	IP	INFLATION	INTEREST
1	100.0000	0.000000	0.000000	0.000000
3	91.67560	5.060463	3.185595	0.078345
6	81.75615	5.787003	12.29351	0.163327
12	75.63998	6.348340	15.63906	2.372621
Variance Decomposition of IP:				
Period	REAL	IP	INFLATION	INTEREST
1	4.024533	95.97547	0.000000	0.000000
3	10.79571	81.43531	1.974722	5.794260
6	18.11424	67.30342	1.592002	12.99034
12	14.86609	57.61012	20.64216	6.881625
Variance Decomposition of INFLATION:				
Period	REAL	IP	INFLATION	INTEREST
1	1.619570	0.079975	98.30046	0.000000
3	2.668755	0.401791	94.44775	2.481709
6	3.310893	3.575089	85.23039	7.883632
12	2.903699	19.78710	63.53426	13.77495
Variance Decomposition of INTEREST:				
Period	REAL	IP	INFLATION	INTEREST
1	11.01593	2.752307	1.567216	84.66455
3	14.75610	1.516887	1.770745	81.95627
6	20.08895	3.410473	0.903290	75.59729
12	18.36131	15.40603	5.291526	60.94113
Cholesky Ordering: REAL IP INFLATION INTEREST				

Notes: The VAR system consists of the global factors for Real returns (REAL), Industrial production (IP), Inflation (INFLATION), and Interest rates (INTEREST). Table 4.7 presents the estimation results which are based on the variance decompositions for 34 pooled countries. The shares of different variables at months of 1, 3, 6, and 12 are presented in the table, respectively.

Table 4.8: Factor Loadings of Global Factor

Country	Industrial production	Inflation	Interest	Real returns	Nominal returns
Argentina	3.019	0.727	0.155	1.900	1.880
Australia	1.000	1.000	0.630	1.000	1.000
Austria	4.249	0.770	0.638	1.626	1.638
Belgium	4.299	0.970	0.687	1.458	1.464
Brazil	3.221	8.026	5.522	2.193	2.181
Canada	3.798	0.652	0.958	1.311	1.323
Chile	2.475	1.526	2.653	0.870	0.869
Denmark	4.502	0.397	0.688	1.499	1.513
Finland	6.707	0.779	0.761	1.902	1.912
France	3.549	0.674	0.948	1.573	1.586
Germany	4.971	0.580	0.645	1.744	1.762
Greece	2.709	0.932	2.707	1.783	1.801
Hong Kong	2.293	1.275	1.24	1.567	1.592
Indonesia	0.551	-3.186	3.146	1.691	1.692
Ireland	3.745	1.815	1.074	1.670	1.670
Italy	5.280	0.769	1.786	1.688	1.705
Japan	6.657	0.345	0.138	1.305	1.320
Korea	3.641	0.373	2.332	1.452	1.464
Malaysia	4.582	0.722	0.925	0.976	0.976
Mexico	2.569	0.979	7.358	1.587	1.653
Netherlands	2.528	0.300	0.362	1.861	1.877
New Zealand	2.663	0.789	0.963	0.793	0.795
Norway	0.986	0.378	0.695	1.854	1.871
Peru	2.871	0.773	1.784	1.555	1.580
Philippines	N/A	0.866	1.728	1.404	1.414
Portugal	2.318	0.848	1.271	1.465	1.475
Singapore	4.393	1.239	0.502	1.458	1.459
Spain	5.146	1.197	1.511	1.523	1.534
Sweden	5.907	0.914	1.314	1.685	1.695
Switzerland	3.635	0.718	0.553	1.336	1.346
Taiwan	5.835	1.081	N/A	1.291	1.302
Thailand	3.249	1.262	2.267	1.293	1.308
United Kingdom	2.757	0.879	0.893	1.191	1.201
United States	3.503	1.069	1.029	1.277	1.287
Average	**3.624**	**0.954**	**1.511**	**1.493**	**1.504**

Notes: Table 4.8 presents the factor loadings of global factors for industrial production, inflation, short-term interest and real returns, respectively. The average of factor loadings for pooled countries is also presented.

Table 4.9: R^2 Statistics from VAR Analysis

Country	R^2 (1)	R^2 (2)
Argentina	0.221	0.304
Australia	0.292	0.501
Austria	0.240	0.330
Belgium	0.190	0.292
Brazil	0.170	0.208
Canada	0.206	0.289
Chile	0.225	0.219
Denmark	0.245	0.391
Finland	0.228	0.298
France	0.218	0.276
German	0.189	0.263
Greece	0.341	0.520
Hong Kong	0.240	0.411
Indonesia	0.425	0.496
Ireland	0.302	0.546
Italy	0.222	0.322
Japan	0.111	0.318
Korea	0.355	0.379
Malaysia	0.212	0.242
Mexico	0.178	0.302
Netherlands	0.228	0.432
Norway	0.229	0.300
Peru	0.208	0.298
Portugal	0.211	0.328
Singapore	0.342	0.406
Spain	0.215	0.337
Sweden	0.190	0.245
Switzerland	0.246	0.398
Thailand	0.294	0.354
UK	0.081	0.191
USA	0.280	0.440
Average (1)	**0.236**	**0.343**
Average (2)	**0.229**	**0.356**

Notes: R^2 (1) denotes the R-squared value from the VAR Analysis including country macroeconomic fundamentals and national real returns. R^2 (2) denotes the R-squared value from the VAR Analysis including country macroeconomic fundamentals, global macroeconomic fundamentals and national real returns. Average (1) and (2) denote the average of R^2 statistics for pooled and developed markets, respectively. Some countries are not included for the unavailability of data.

Table 4.10: Variance Decomposition for Country's Stock market real returns

Country	Macro_C	Macro_G	Market
Argentina	7.535	9.360	83.105
Australia	10.940	27.366	61.694
Austria	9.216	10.630	80.154
Belgium	7.726	8.614	83.660
Brazil	4.547	3.597	91.856
Canada	9.766	10.734	79.496
Chile	5.891	6.919	87.190
Denmark	11.410	16.854	71.734
Finland	6.206	7.569	86.225
France	10.726	5.256	84.018
German	7.599	4.696	87.704
Greece	12.839	20.080	67.081
Hong Kong	10.133	18.425	71.443
Indonesia	13.357	11.095	75.548
Ireland	16.861	22.770	60.369
Italy	5.091	12.721	82.188
Japan	8.815	18.138	73.047
Korea	20.811	7.398	71.791
Malaysia	4.817	3.454	91.729
Mexico	4.535	12.210	83.255
Netherlands	17.870	13.665	68.466
Norway	14.122	5.743	80.135
Peru	2.726	12.833	84.441
Portugal	5.172	15.276	79.552
Singapore	15.033	9.033	75.935
Spain	8.269	12.341	79.390
Sweden	5.928	8.277	85.795
Switzerland	10.786	16.065	73.149
Thailand	19.00	4.613	76.384
UK	4.392	9.434	86.174
USA	13.907	19.066	67.027
Average (1)	**9.872**	**11.749**	**78.379**
Average (2)	**10.128**	**13.307**	**76.565**

Notes: The results are the variance decomposition after 12 months for explanatory variables. Variable Macro_C is the sum of the variance shares of each country's stock market fluctuations attributable to its own macro fluctuations, represented by industrial production, inflation and interest rates. Variable Macro_G is the sum of the variance shares of each country's stock market fluctuations attributable to global macro fluctuations, represented by industrial production, inflation and interest rates. Variable Market is the variance share attributable to the market's own fluctuations. Average (1) and (2) denote the average of variance shares for pooled and developed markets, respectively.

Table 4.11: Results of OLS Analysis

Dependent variable: Variance share of global factor for real returns		
	Coefficients (1)	Coefficients (2)
Constant	31.890	47.489
IP	0.142 (0.333)	0.143 (0.302)
Inflation	0.321 (0.059)	0.175 (0.293)
Interest	0.199 (0.300)	0.085 (0.677)
R-squared	0.483	0.259
Adj R-squared	0.427	0.148
No. of obs.	32	24

Notes: Table 4.11 presents the estimation results from the regression of the variance share of global factor for real returns on the variance shares of global macroecnomi factors, represented by industrial production, inflation rate, and interest rate. The Columns of Coefficients (1) and (2) present the results for 32 pooled and 24 developed countries, respectively. P-values are presented in parentheses.

Table 4.12: Variance Decomposition (Nominal Returns)

Variance Decomposition of NOMINAL:				
Period	NOMINAL	IP	INFLATION	INTEREST
1	100.0000	0.000000	0.000000	0.000000
3	91.79738	5.099019	3.019973	0.083626
6	82.12727	5.861362	11.84332	0.168048
12	76.27850	6.361278	15.08992	2.270299
Variance Decomposition of IP:				
Period	NOMINAL	IP	INFLATION	INTEREST
1	3.990365	96.00964	0.000000	0.000000
3	10.74931	81.48684	1.978723	5.785122
6	18.06282	67.36142	1.590637	12.98512
12	14.83635	57.64152	20.65208	6.870047
Variance Decomposition of INFLATION:				
Period	NOMINAL	IP	INFLATION	INTEREST
1	1.648540	0.078041	98.27342	0.000000
3	2.675741	0.410944	94.41719	2.496129
6	3.292963	3.613714	85.17478	7.918540
12	2.875755	19.81444	63.47620	13.83360
Variance Decomposition of INTEREST:				
Period	NOMINAL	IP	INFLATION	INTEREST
1	10.96049	2.772824	1.563689	84.70300
3	14.72411	1.533348	1.764721	81.97782
6	20.03274	3.441637	0.899448	75.62617
12	18.31332	15.44214	5.293162	60.95137
Cholesky Ordering: REAL IP INFLATION INTEREST				

Notes: The VAR system consists of the global factors for Nominal returns (NOMINAL), Industrial production (IP), Inflation (INFLATION), and Interest rates (INTEREST). Table 4.12 presents the estimation results which are based on the variance decompositions for pooled countries. The shares of different variables at months of 1, 3, 6, and 12 are presented in the table, respectively.

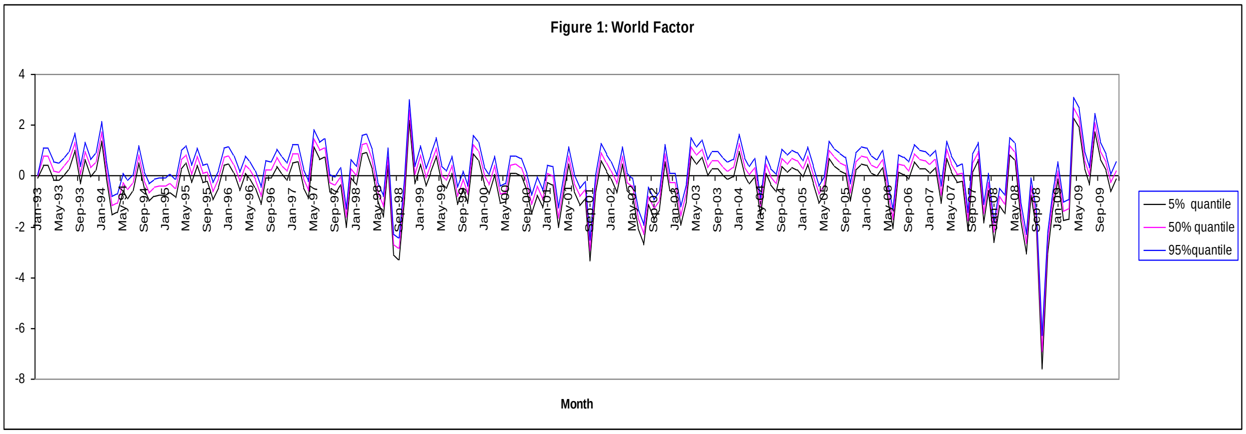
Table 4.13: Variance Decomposition (Real Returns)

Variance Decomposition of REAL:				
Period	REAL	IP	INFLATION	INTEREST
1	100.0000	0.000000	0.000000	0.000000
3	96.26288	1.185517	1.870185	0.681419
6	84.01836	5.500179	8.880177	1.601281
12	73.09180	5.560488	11.51811	9.829600
Variance Decomposition of IP:				
Period	REAL	IP	INFLATION	INTEREST
1	3.090329	96.90967	0.000000	0.000000
3	8.379021	87.39097	2.618960	1.611044
6	15.13477	70.68445	3.881529	10.29925
12	22.13497	59.20338	9.948390	8.713262
Variance Decomposition of INFLATION:				
Period	REAL	IP	INFLATION	INTEREST
1	1.529026	0.064642	98.40633	0.000000
3	4.300422	1.656758	92.08801	1.954813
6	8.550291	6.244344	78.91665	6.288716
12	12.61908	5.290789	67.16464	14.92550
Variance Decomposition of INTEREST:				
Period	REAL	IP	INFLATION	INTEREST
1	10.78297	0.192934	2.252335	86.77176
3	16.44436	0.209480	2.146747	81.19941
6	24.30608	3.175385	0.826698	71.69184
12	29.34071	9.026971	1.522340	60.10997
Cholesky Ordering: REAL IP INFLATION INTEREST				

Notes: The VAR system consists of the global factors for Real returns (REALl), Industrial production (IP), Inflation (INFLATION), and Interest rates (INTEREST). Table 4.13 presents the estimation results which are based on the variance decompositions for OECD countries. The shares of different variables at months of 1, 3, 6, and 12 are presented in the table, respectively.

Figures

Figure 2.1: World Factor



Notes: Figure 2.1 plots the median of the posterior distribution of world factor for main stock market returns in the world, along with 5-percent and 95-percent quantile over 1993-2009.

Figure 2.2: Regional Factors

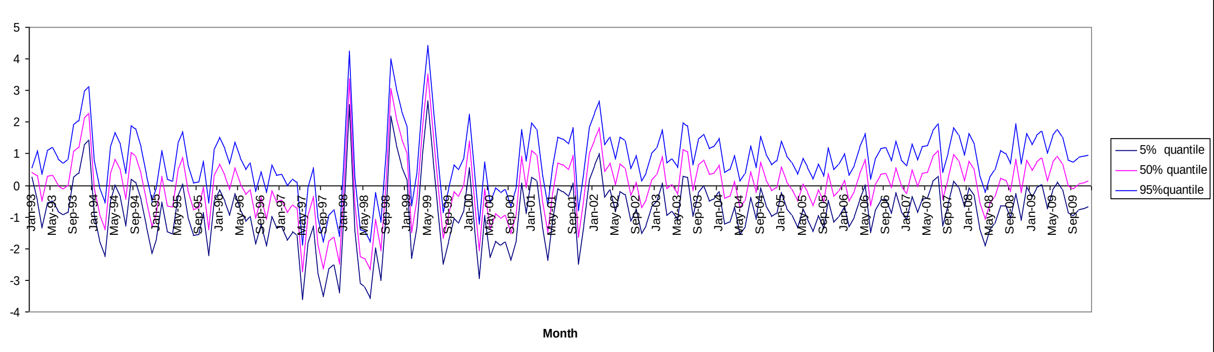


Figure 2.1: Asian (Emerging) Regional Factor

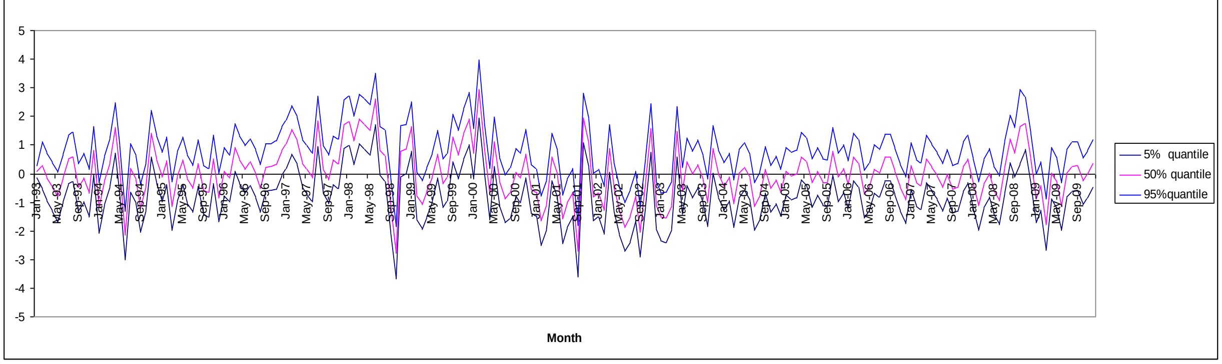


Figure 2.2: European Regional Factor

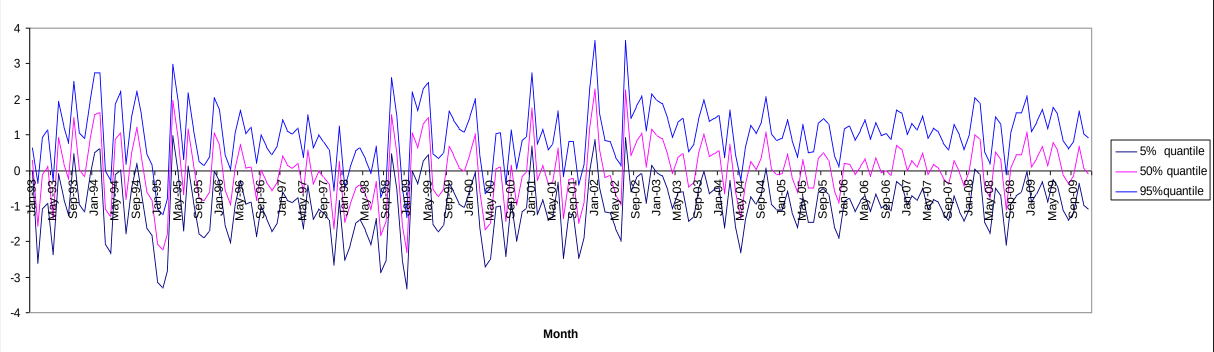


Figure 2.3: South American Regional Factor

Notes: Figures 2.2.1-2.2.3 plot the median of the posterior distribution of 5 different regional factors for the markets in Oceania, Asian, South East Asia, European Union, and South America , along with 5-percent and 95-percent quantile over 1993-2009, respectively.

Figure 2.3: World Factor, Regional Factor and Actual Stock Market Returns

Figure 3.1 United States

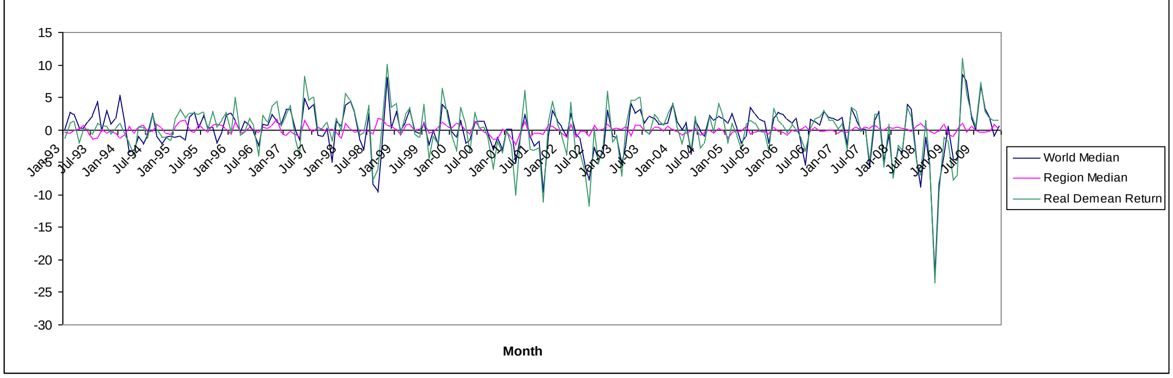


Figure 3.2 Thailand

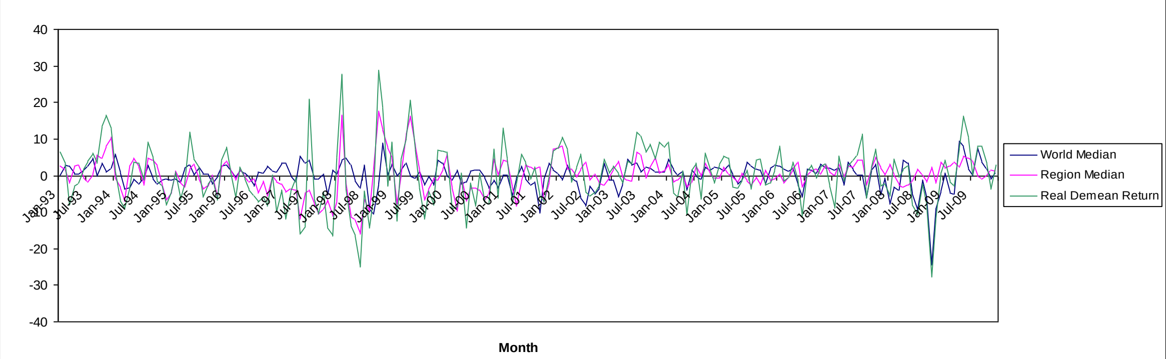
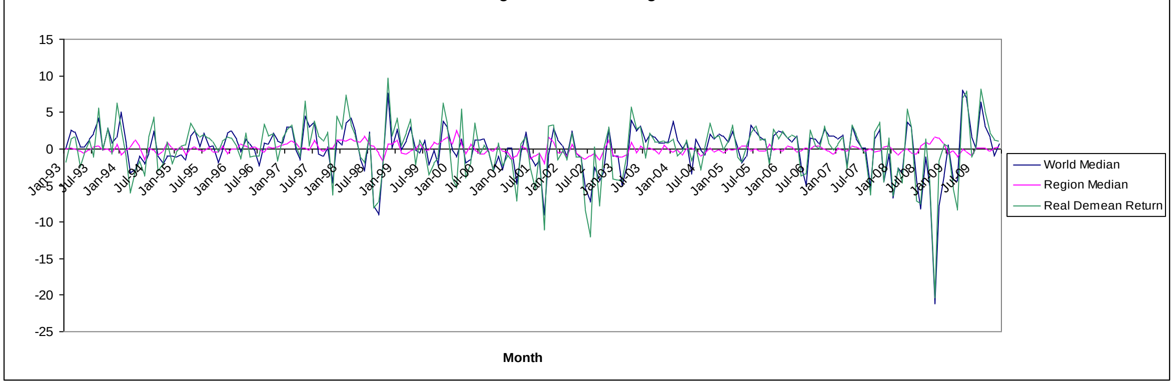
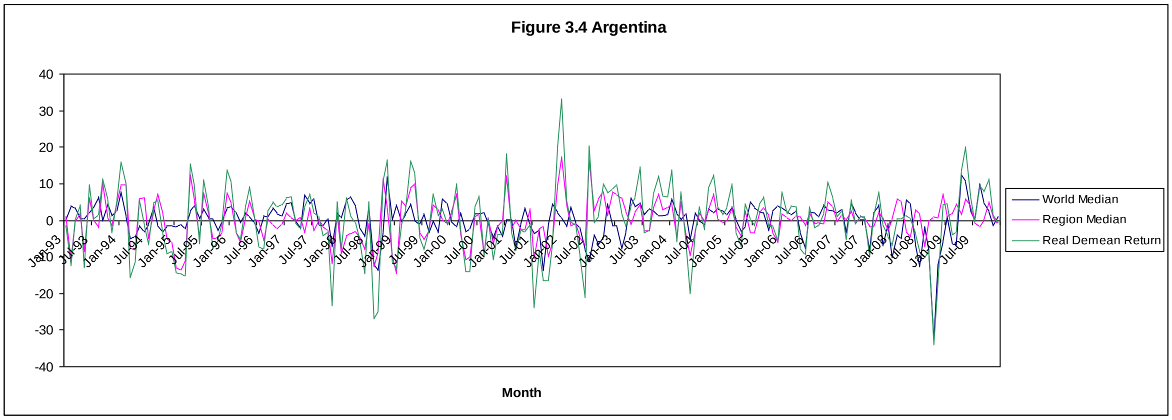


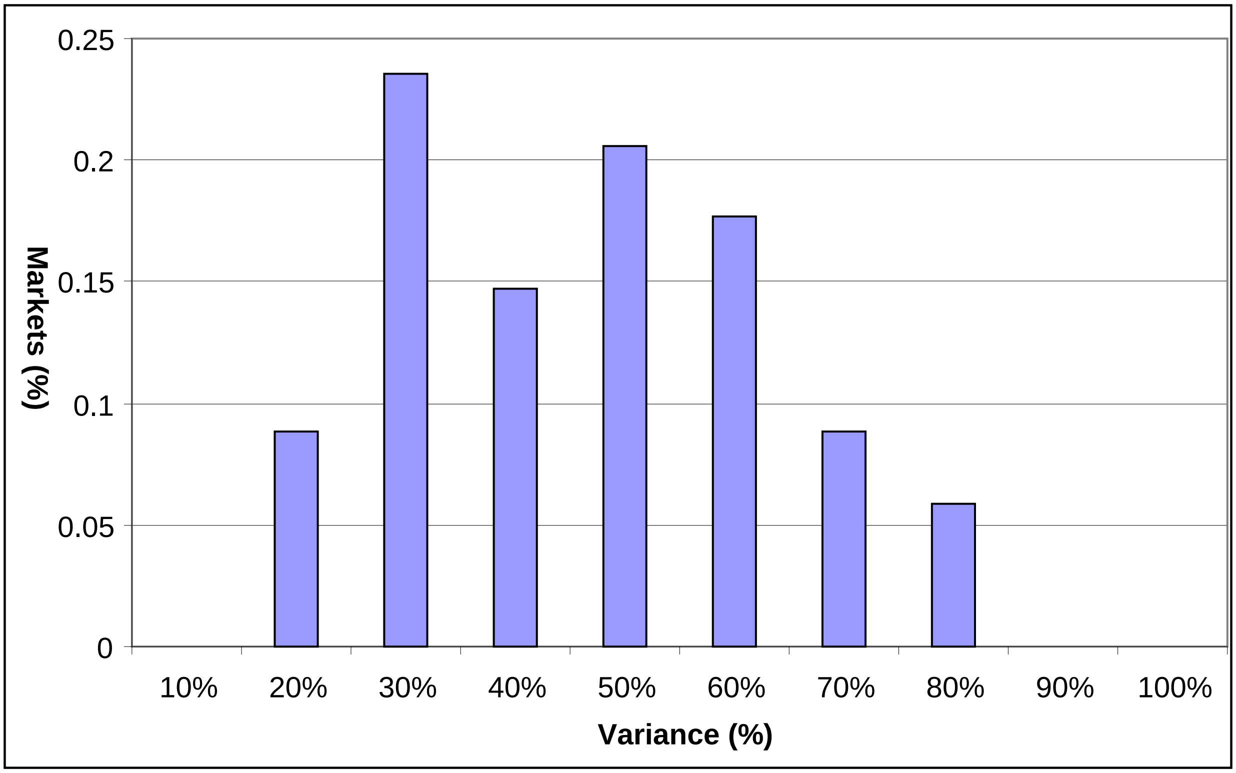
Figure 3.3 United Kingdom





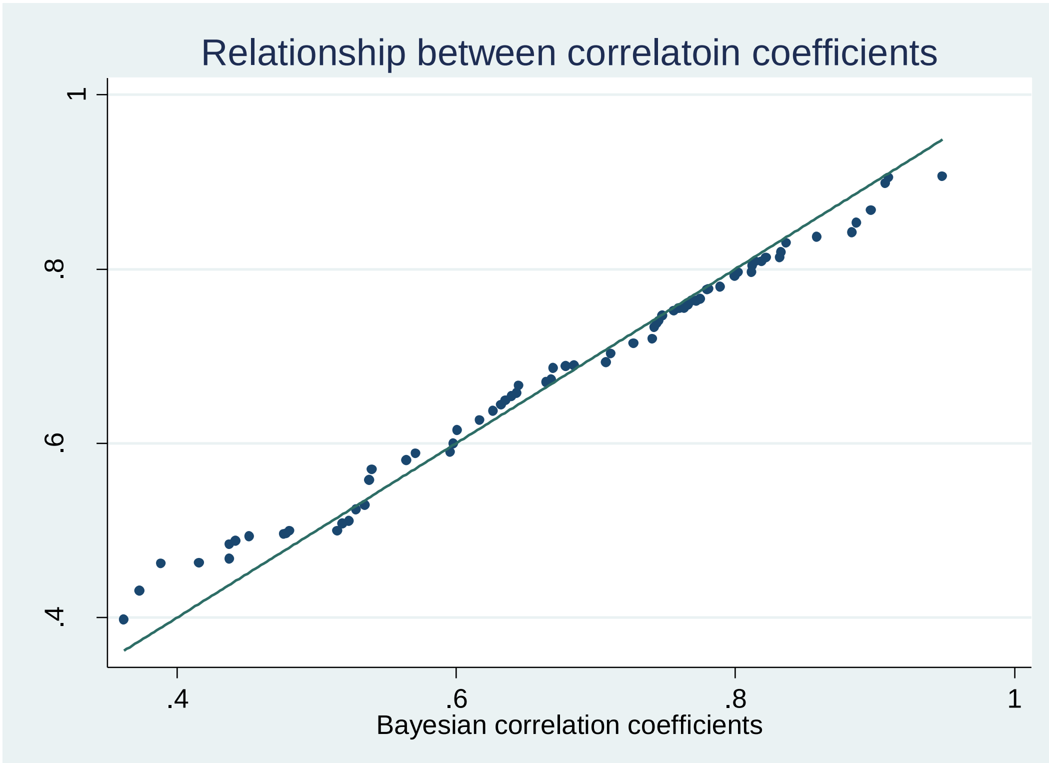
Notes: Figures 2.3.1-2.3.4 plot the actual stock market returns along with the Median of world and regional factors for the USA, Thailand, UK, and Argentina, respectively. The world and regional factors are multiplied by their respective median factor loading, respectively.

Figure 2.4: Return Variance Due to World Factor



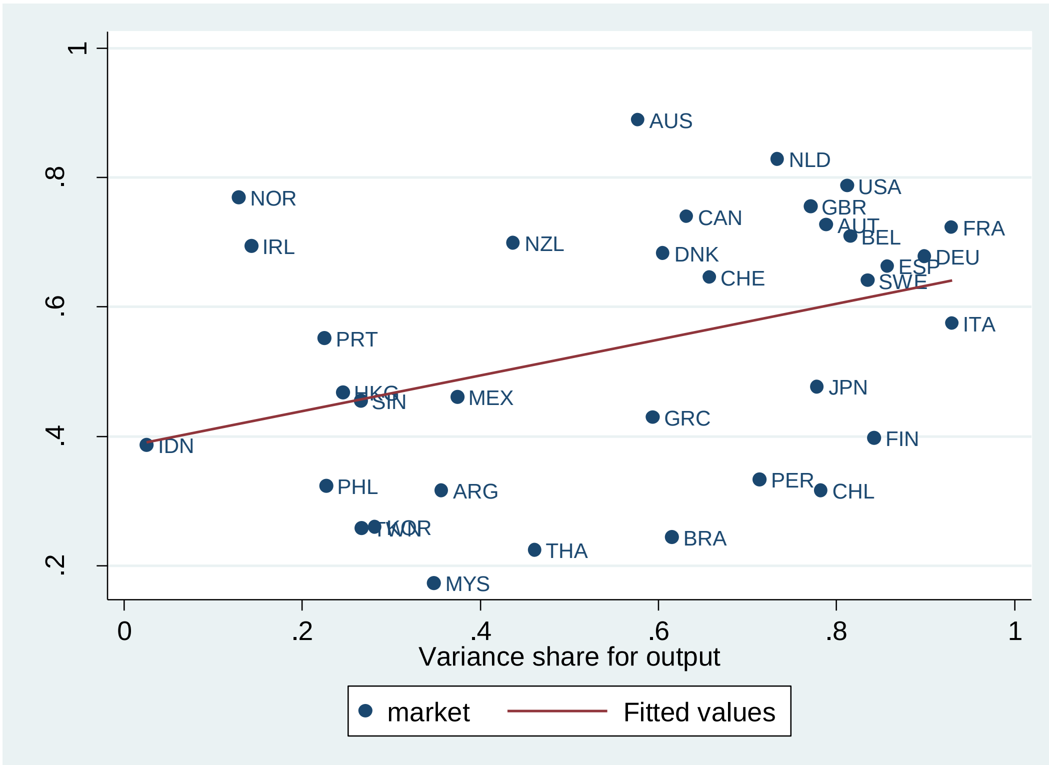
Notes: The histogram in Figure 2.4 plots the frequency of the amount of stock markets in which the variance of stock market returns is attributable to the world factor in different levels.

Figure 2.5: Relationship between Correlation Coefficients



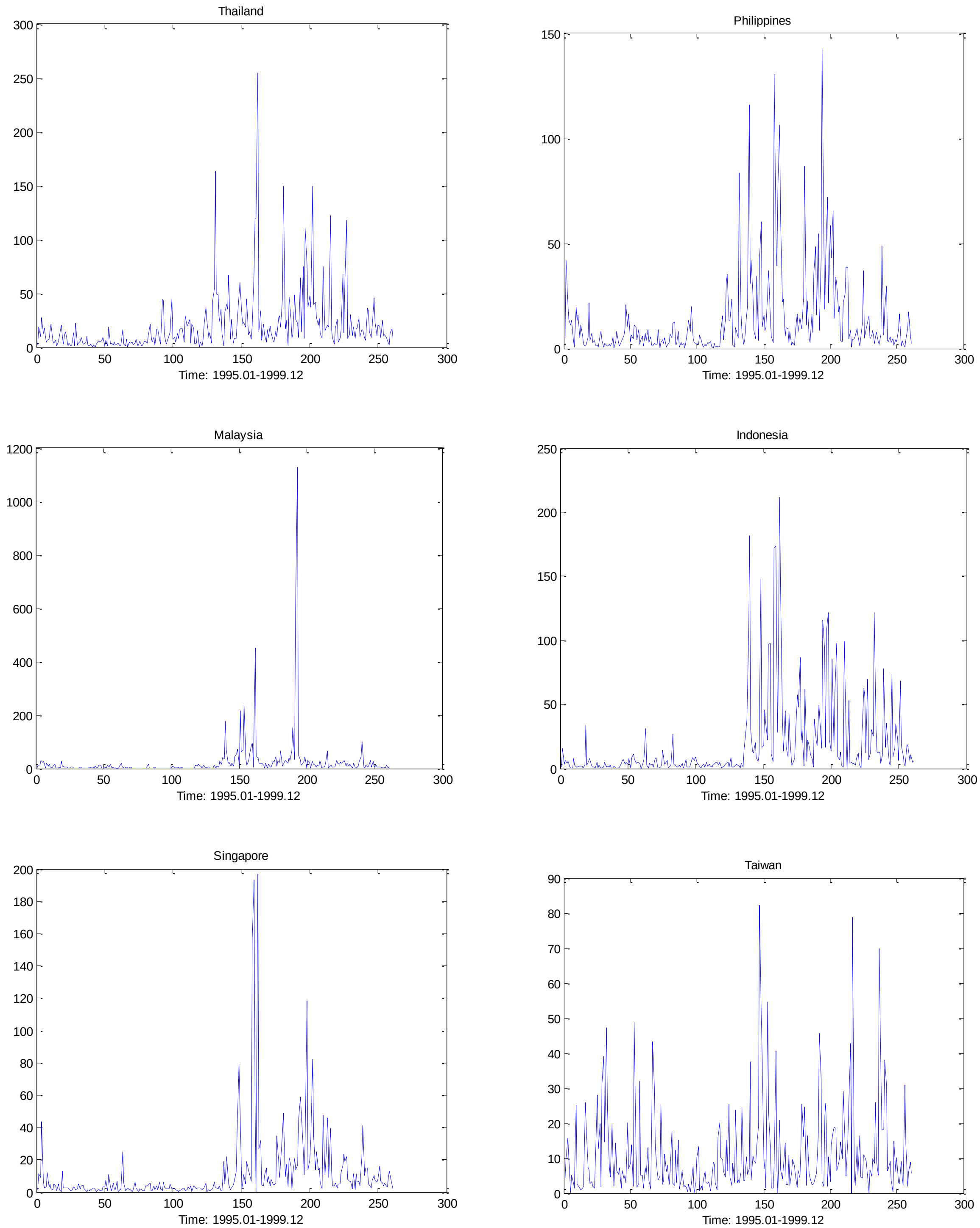
Notes: Figure 2.5 plots the relationship between simple correlation coefficients and Bayesian correlation coefficients. Here simple correlation coefficients refer to the simple pair-wise correlations coefficients. Bayesian coefficients are the bilateral correlation coefficients on the basis of the Bayesian dynamic factor model for stock markets within each region.

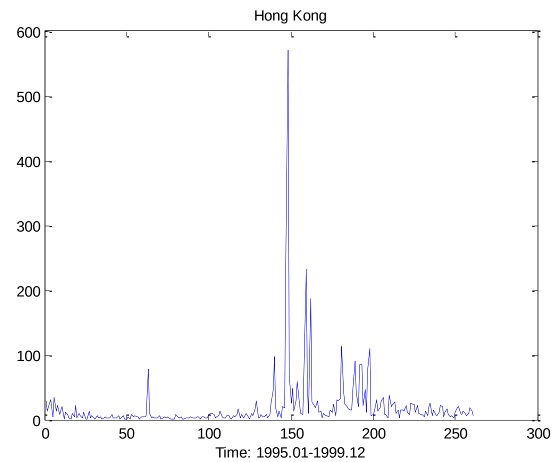
Figure 2.6: Relationship between Variance Shares of Global Factor

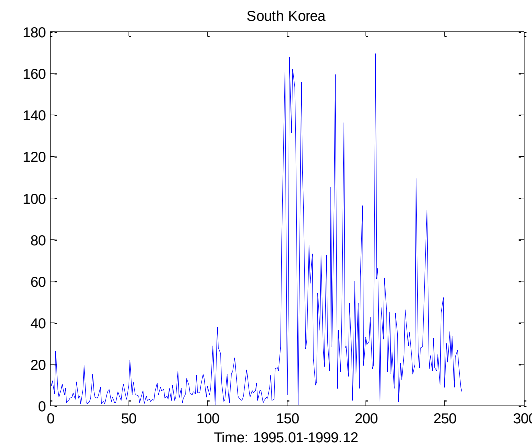


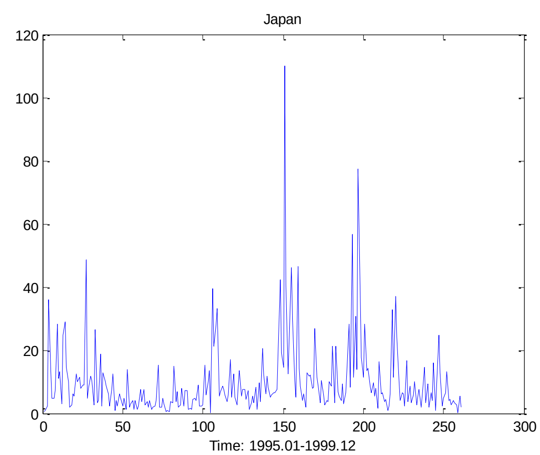
Notes: Figure 2.6 plots the relationship between the variance share of global factor for stock markets and for output production. The variance share for markets refers to the variance of stock market returns attributable to the global factor, which measure to what extent each stock market co-moves with global stock markets. Similarly, the variance share for output refers to the variance of output attributable the global factor, which measure to what extent a country commoves with the world business cycle.

Figure 3.1: Realized Volatility Indices (1995.01-1999.12)



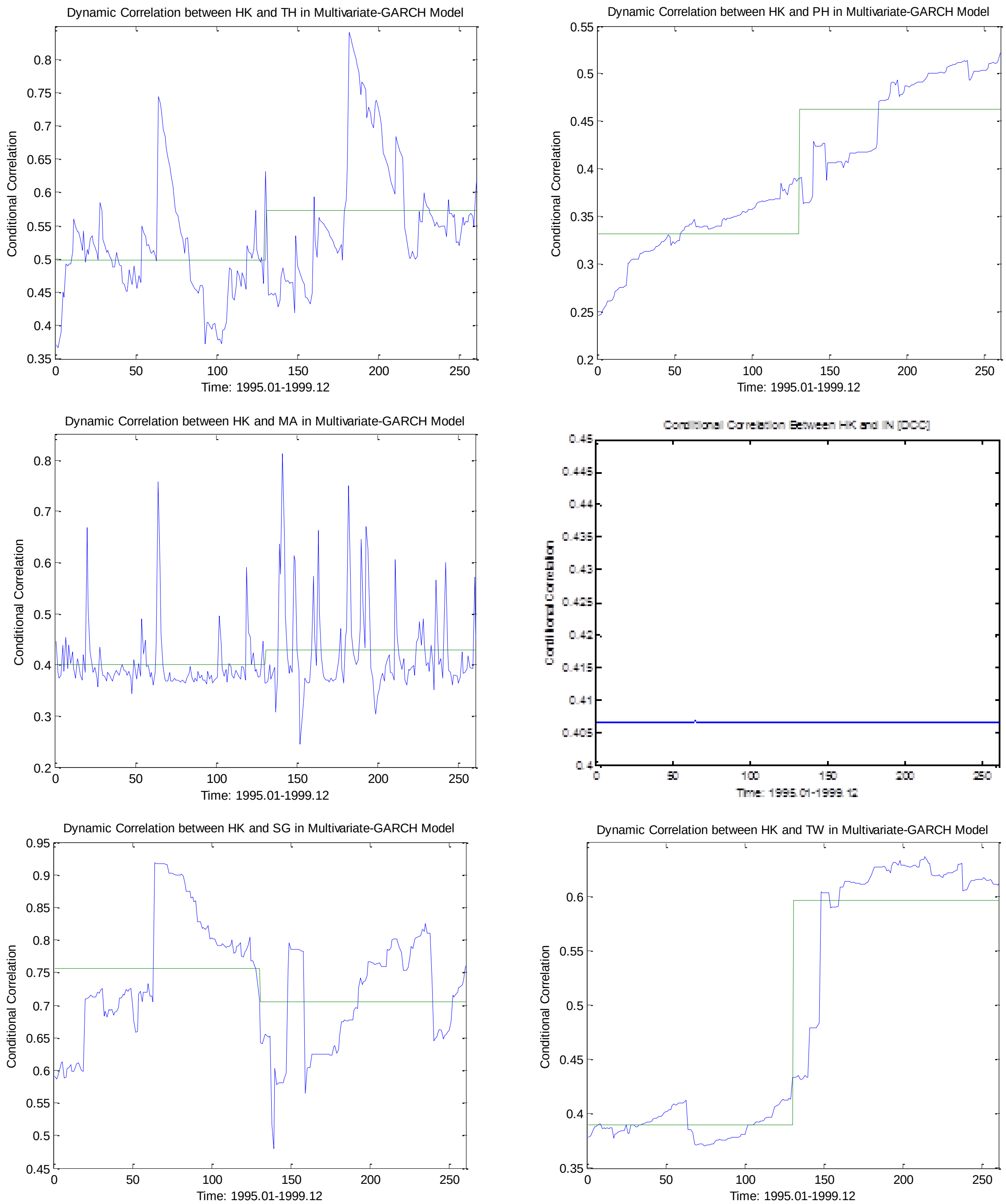


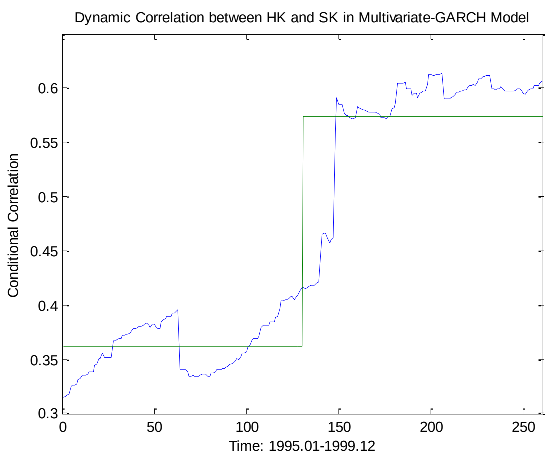


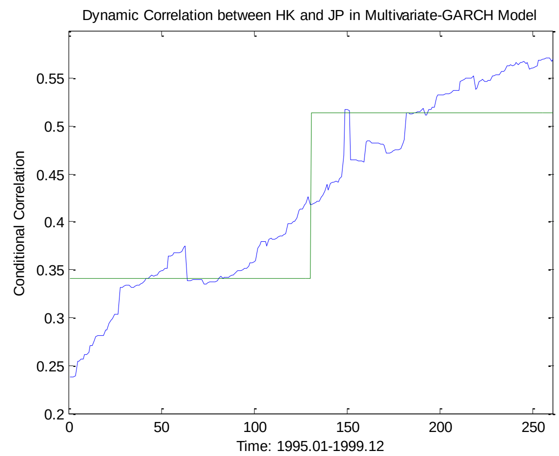


Notes: Figures plot the weekly realized volatility of Thailand, Philippines, Malaysia, Indonesia, Singapore, Taiwan, Hong Kong, South Korea, and Japan markets over 1995-1999, respectively.

Figure 3.2.1: Dynamic Correlation between Hong Kong and other Asian Markets in DCC-GARCH Model

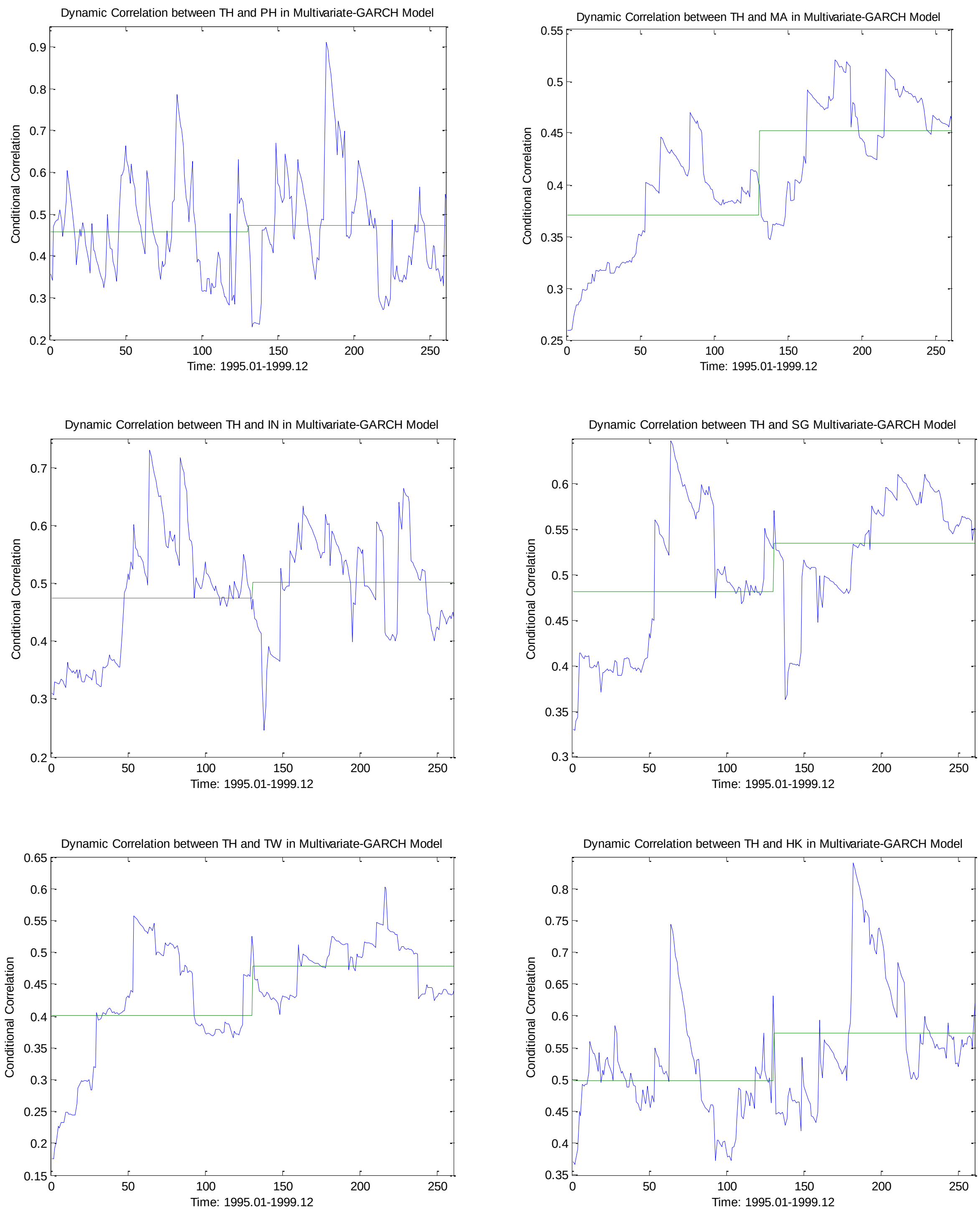


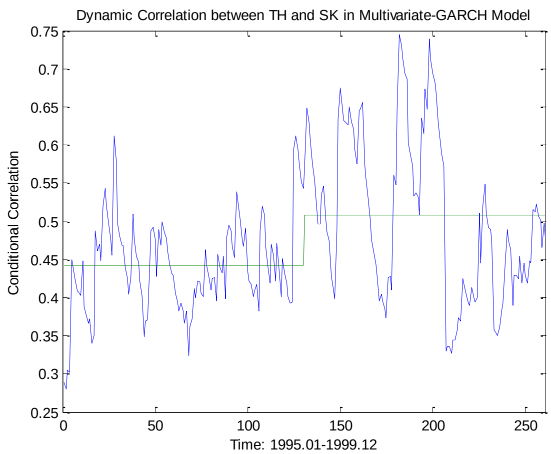


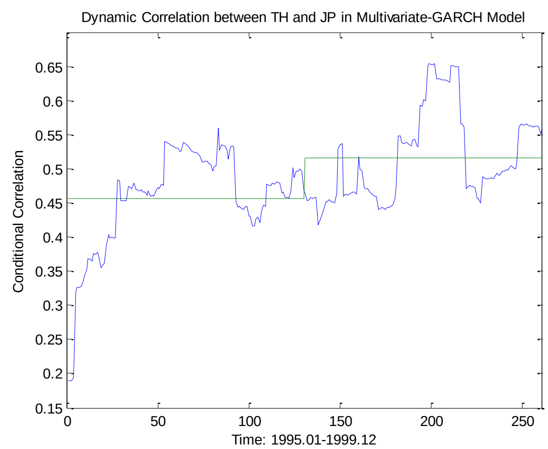


Notes: Figures plot the dynamic correlation between the realized volatility of Hong Kong Market and those of other Asian markets in DCC-GARCH Model. The green line represents the average of the correlation coefficients between Hong Kong and other Asian markets before and after crisis, respectively, which is based on the DCC-GARCH model.

Figure 3.2.2: Dynamic Correlation between Thailand and other Asian Markets in DCC-GARCH Model

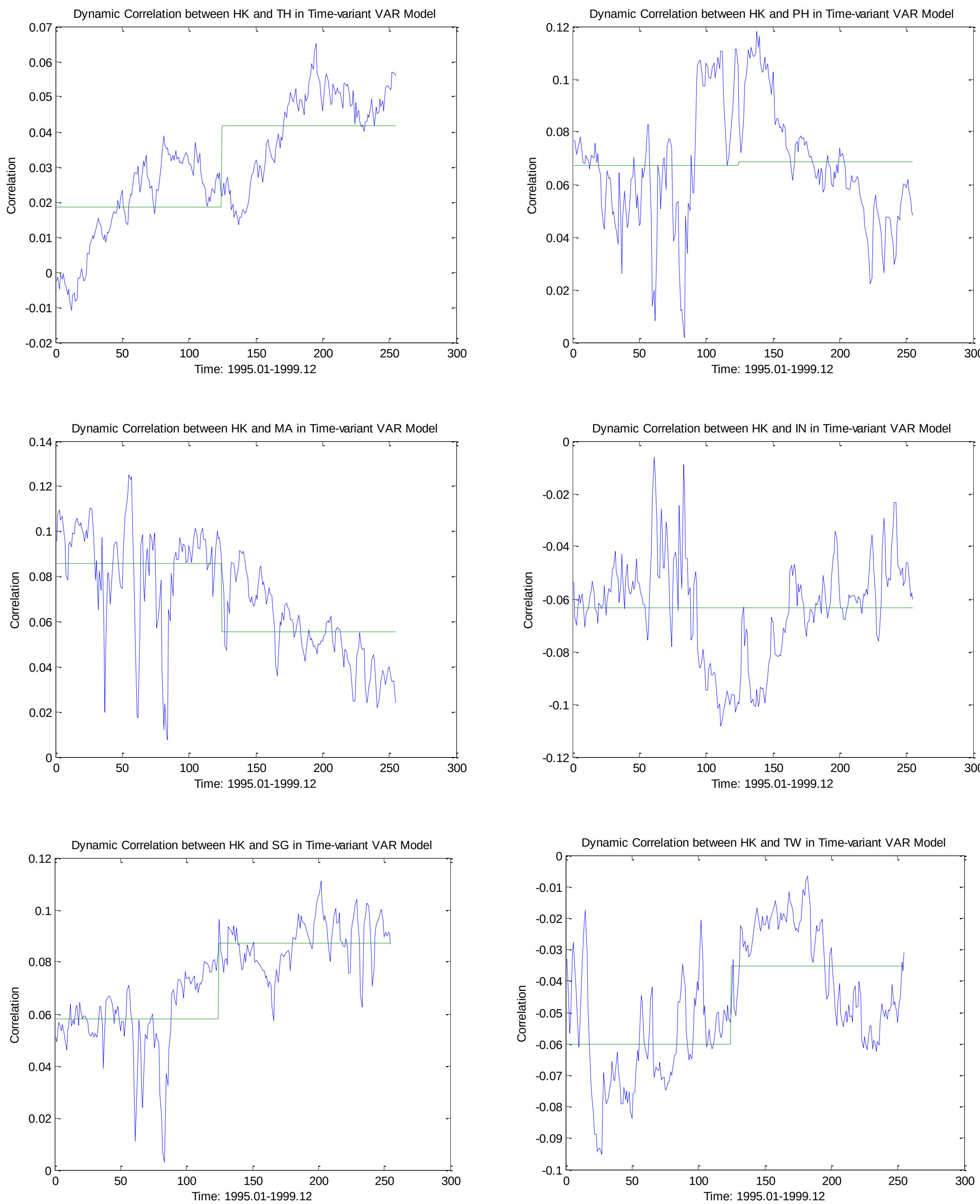


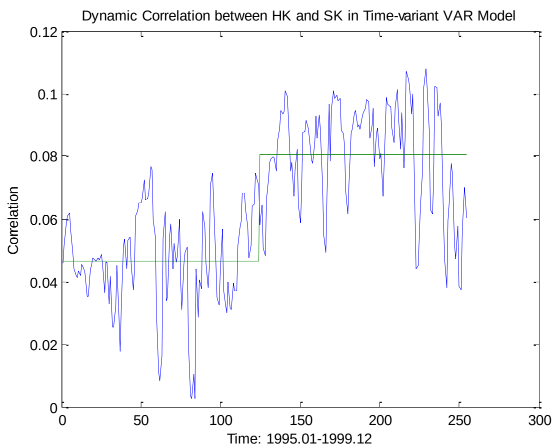


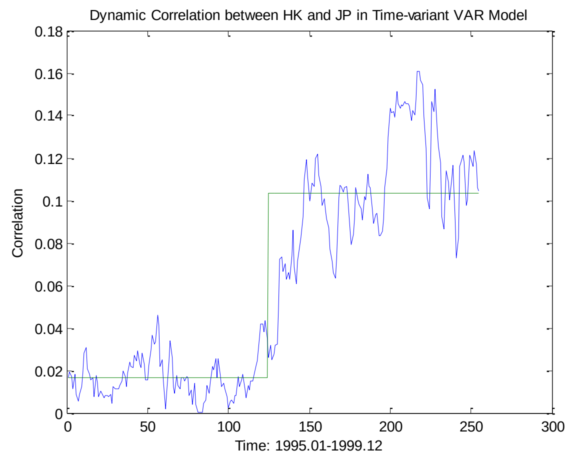


Notes: Figures plot the dynamic correlation between the realized volatility of Thailand Market and those of other Asian markets in DCC-GARCH Model. The green line represents the averages of the correlation coefficients between Thailand and other Asian markets before and after crisis, respectively, which is based on the DCC-GARCH model.

Figure 3.3.1: Dynamic Correlation between Hong Kong and other Asian Markets in Time-varying VAR Model

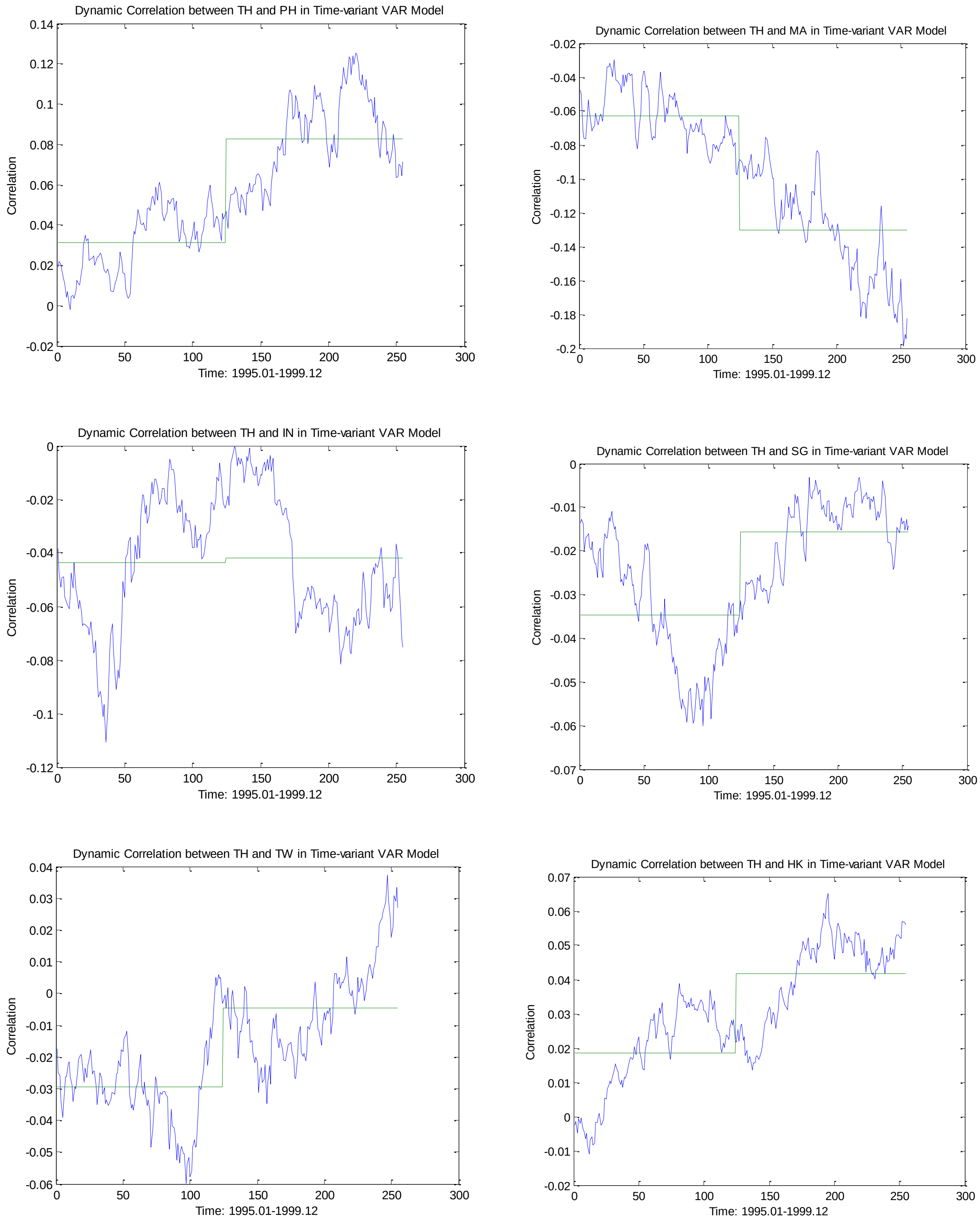


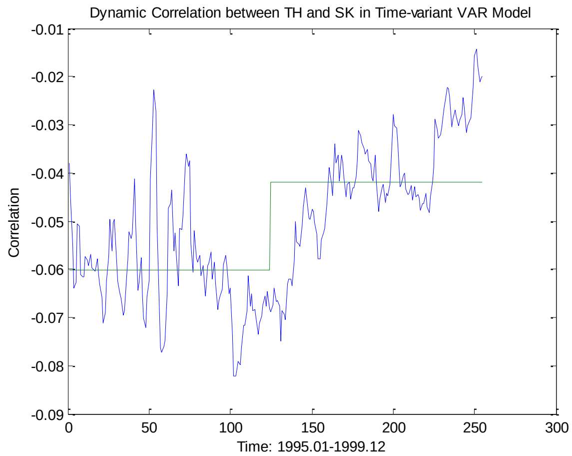


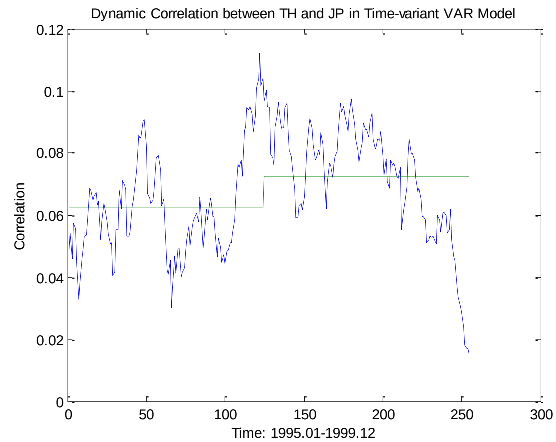


Notes: Figures plot the dynamic correlation between the realized volatility of Hong Kong Market and those of other Asian markets in Time-varying VAR model. The green line represents the average of the correlation coefficients between Hong Kong and other Asian markets before and after crisis, respectively, which is based on the Time-varying VAR model.

Figure 3.3.2: Dynamic Correlation between Thailand and other Asian Markets in Time-varying VAR Model

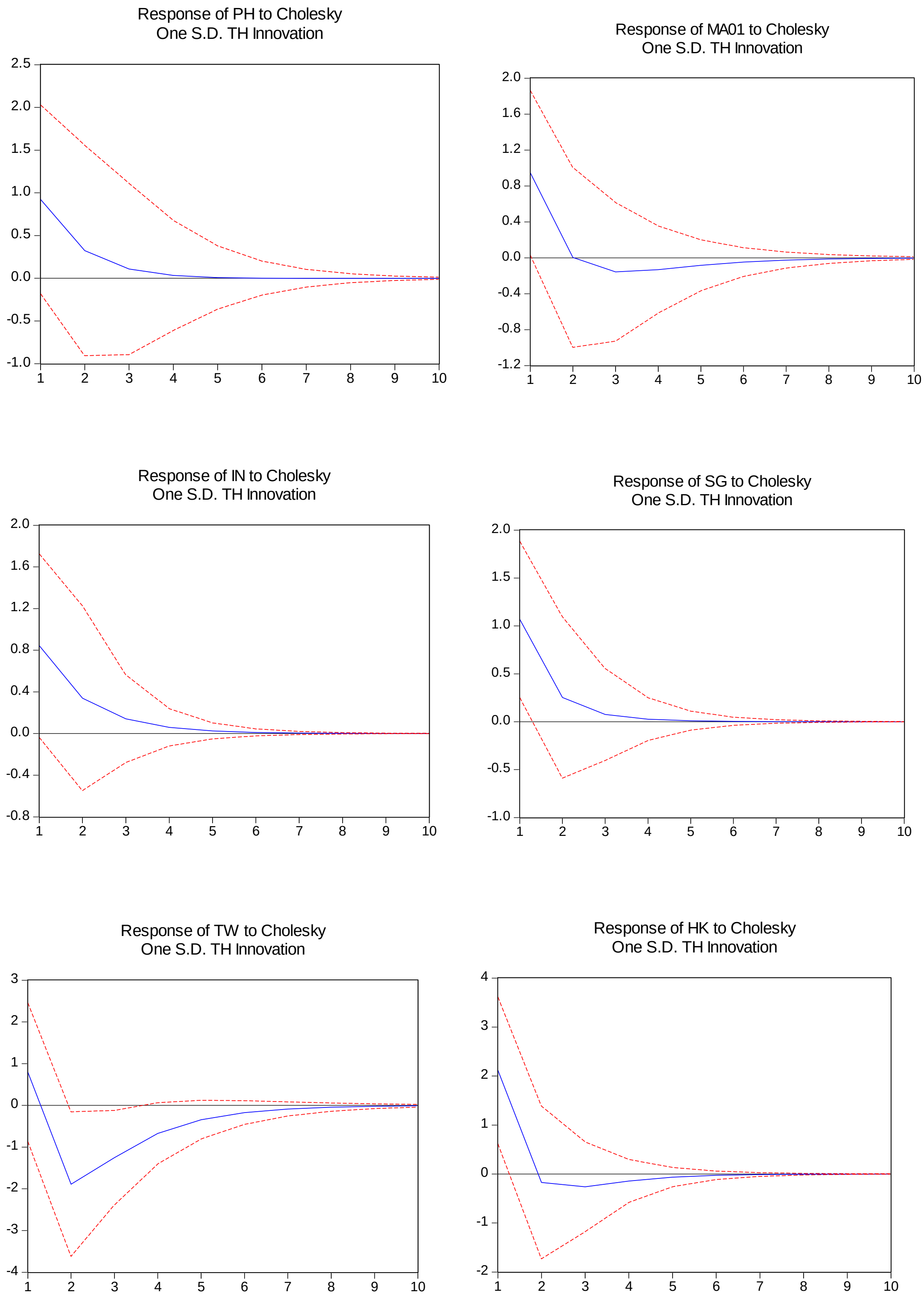


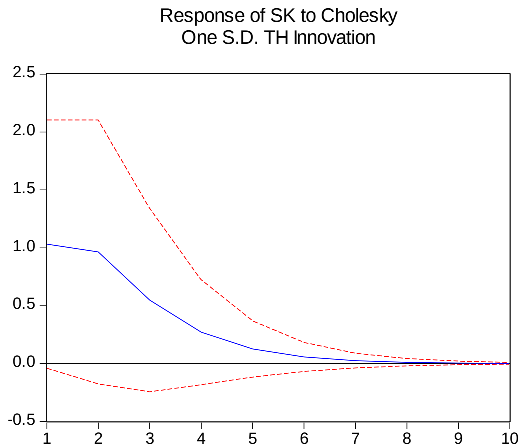




Notes: Figures plot the dynamic correlation between the realized volatility of Thailand Market and those of other Asian markets in Time-varying VAR model. The green line represents the average of the correlation coefficients between Thailand and other Asian markets before and after crisis, respectively, which is based on the Time-varying VAR model.

Figure 3.4.1: Impulse Response Analysis (Realized Volatility Index before Crisis)




Response of SK to Cholesky
One S.D. TH Innovation
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
1
2
3
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5
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8
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10

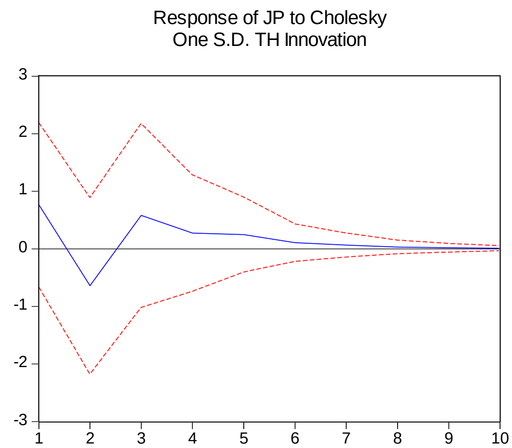
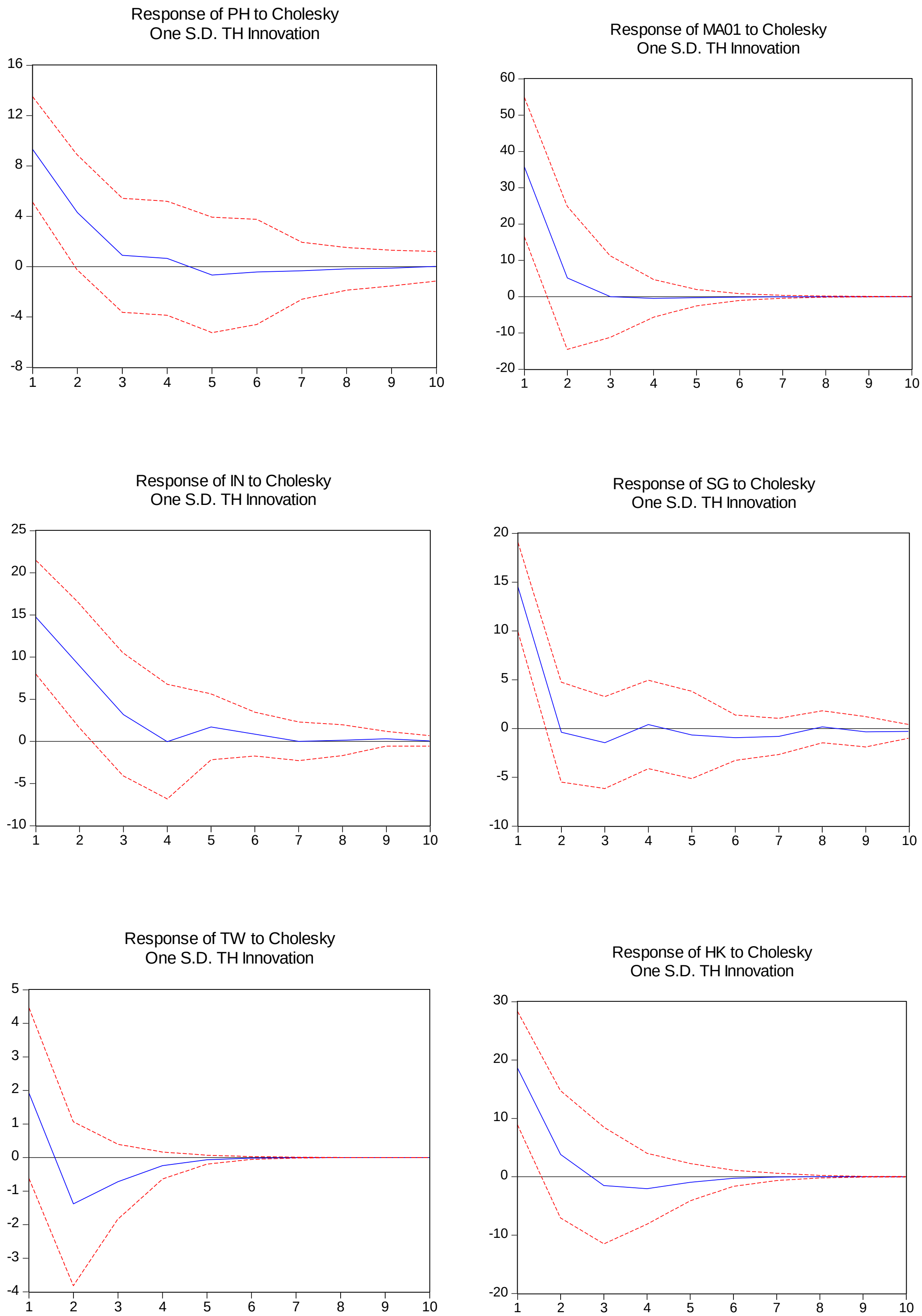
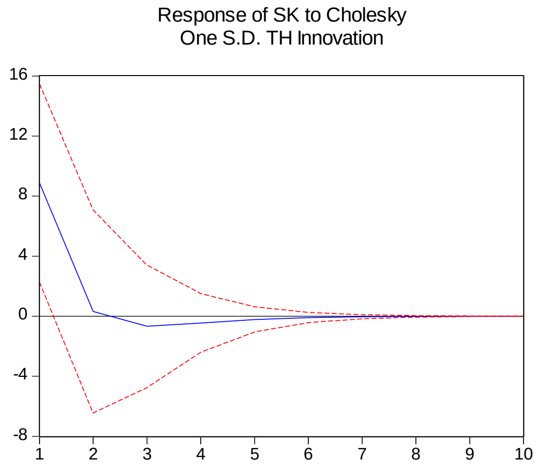

Response of JP to Cholesky
One S.D. TH Innovation
3
2
1
0
-1
-2
-3
1
2
3
4
5
6
7
8
9
10

Figure 3.4.2: Impulse Response Analysis (Realized Volatility Index after Crisis)




Response of SK to Cholesky
One S.D. TH Innovation
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12
8
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-4
-8
1
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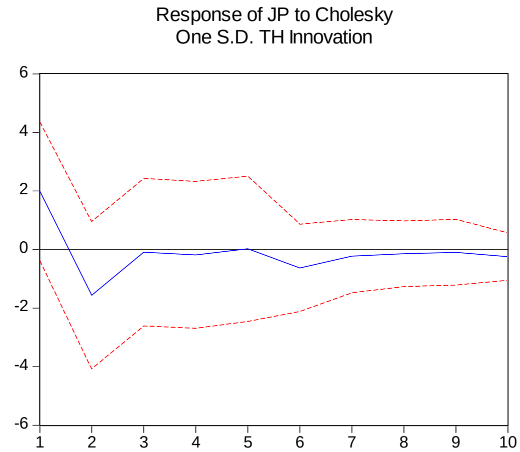
Response of JP to Cholesky
One S.D. TH Innovation
6
4
2
0
-2
-4
-6
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2
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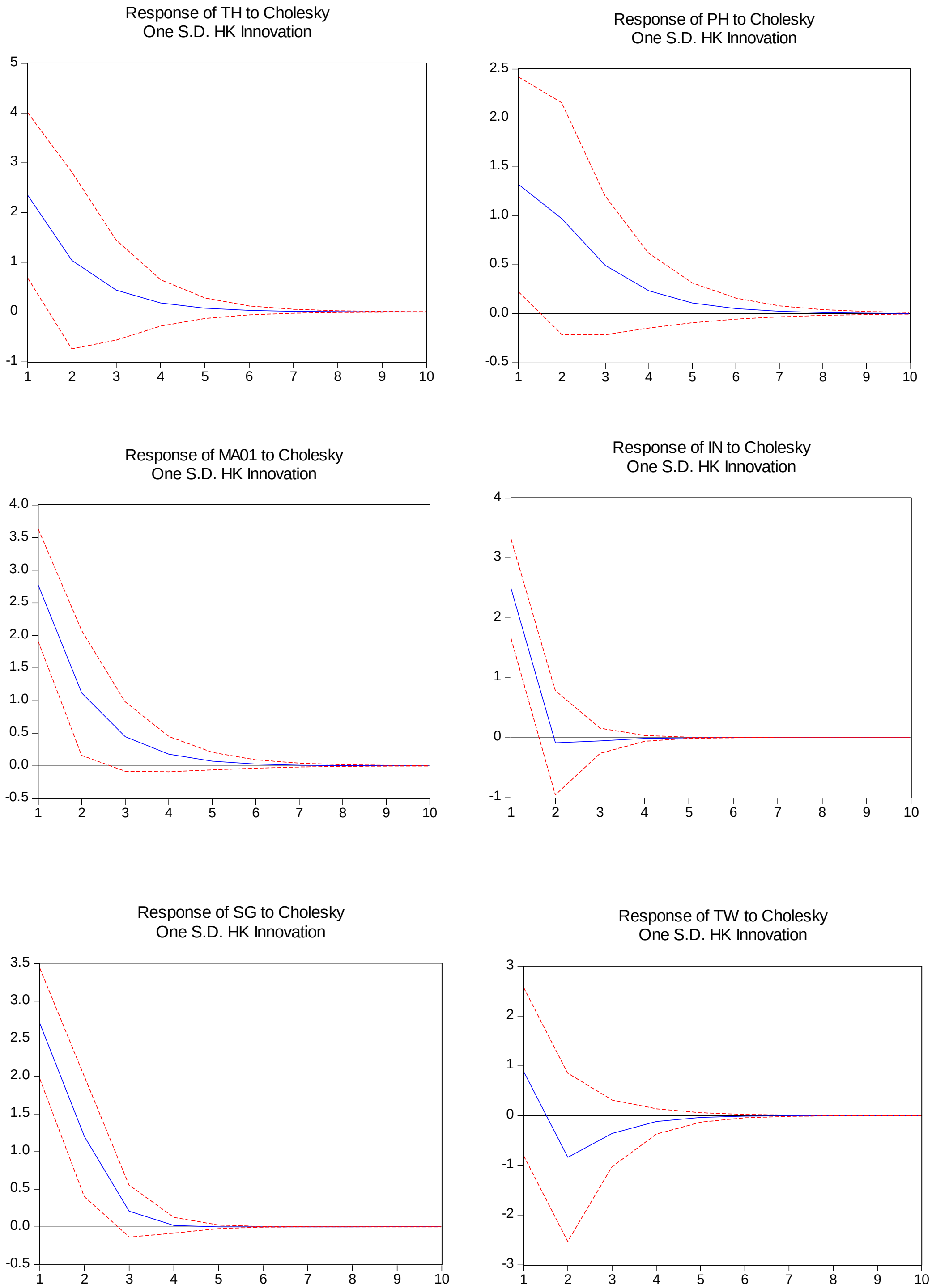
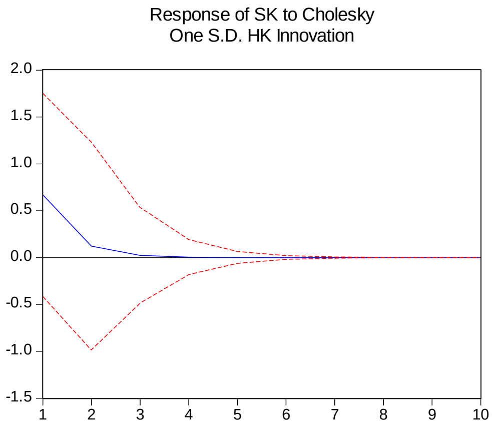
8
9
10

Figure 3.4.3: Impulse Response Analysis (Realized Volatility Index before Crisis)




Response of SK to Cholesky
One S.D. HK Innovation
2.0
1.5
1.0
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-0.5
-1.0
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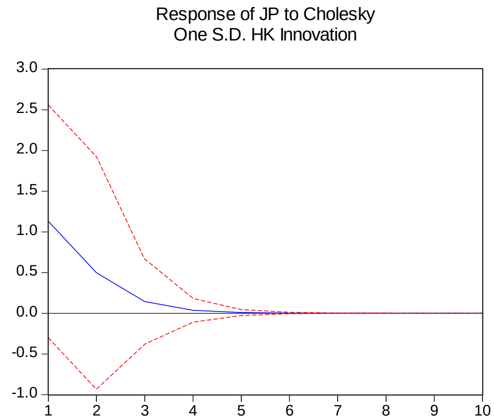
Response of JP to Cholesky
One S.D. HK Innovation
3.0
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
-1.0
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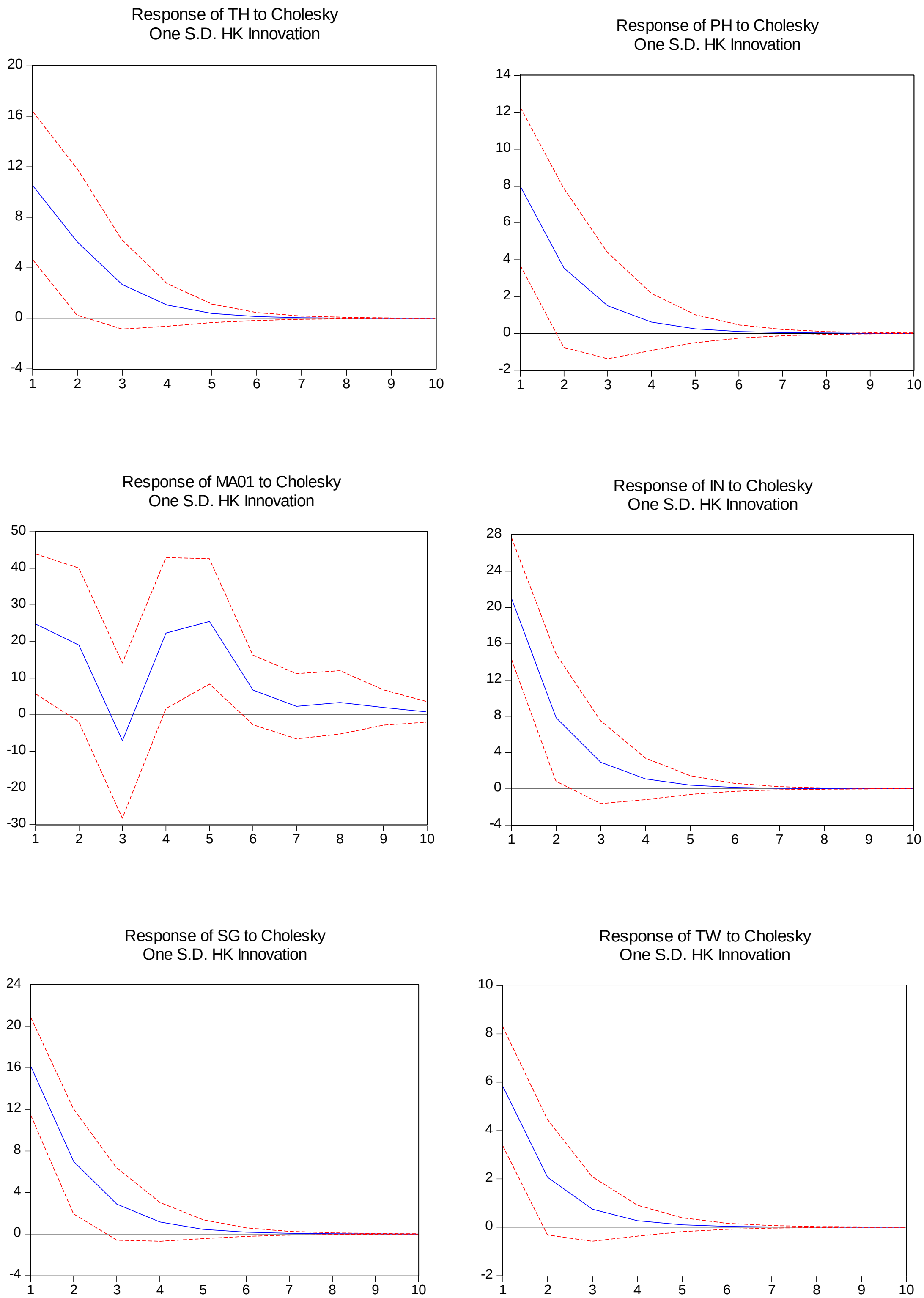
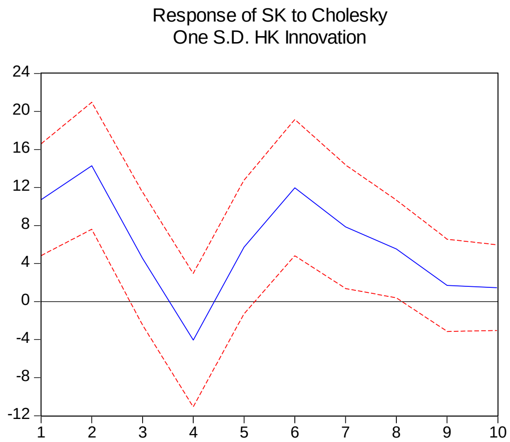
Figure 3.4.4: Impulse Response Analysis (Realized Volatility Index after Crisis)




Response of SK to Cholesky
One S.D. HK Innovation
24
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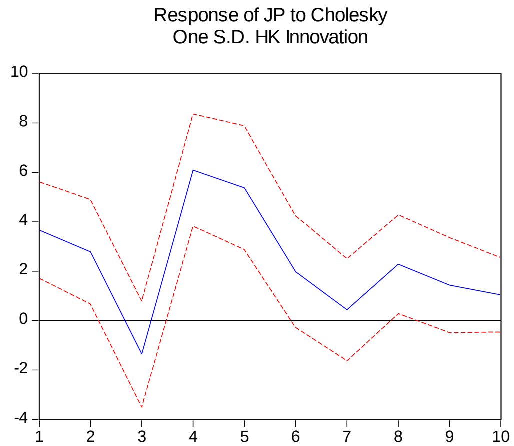
Response of JP to Cholesky
One S.D. HK Innovation
10
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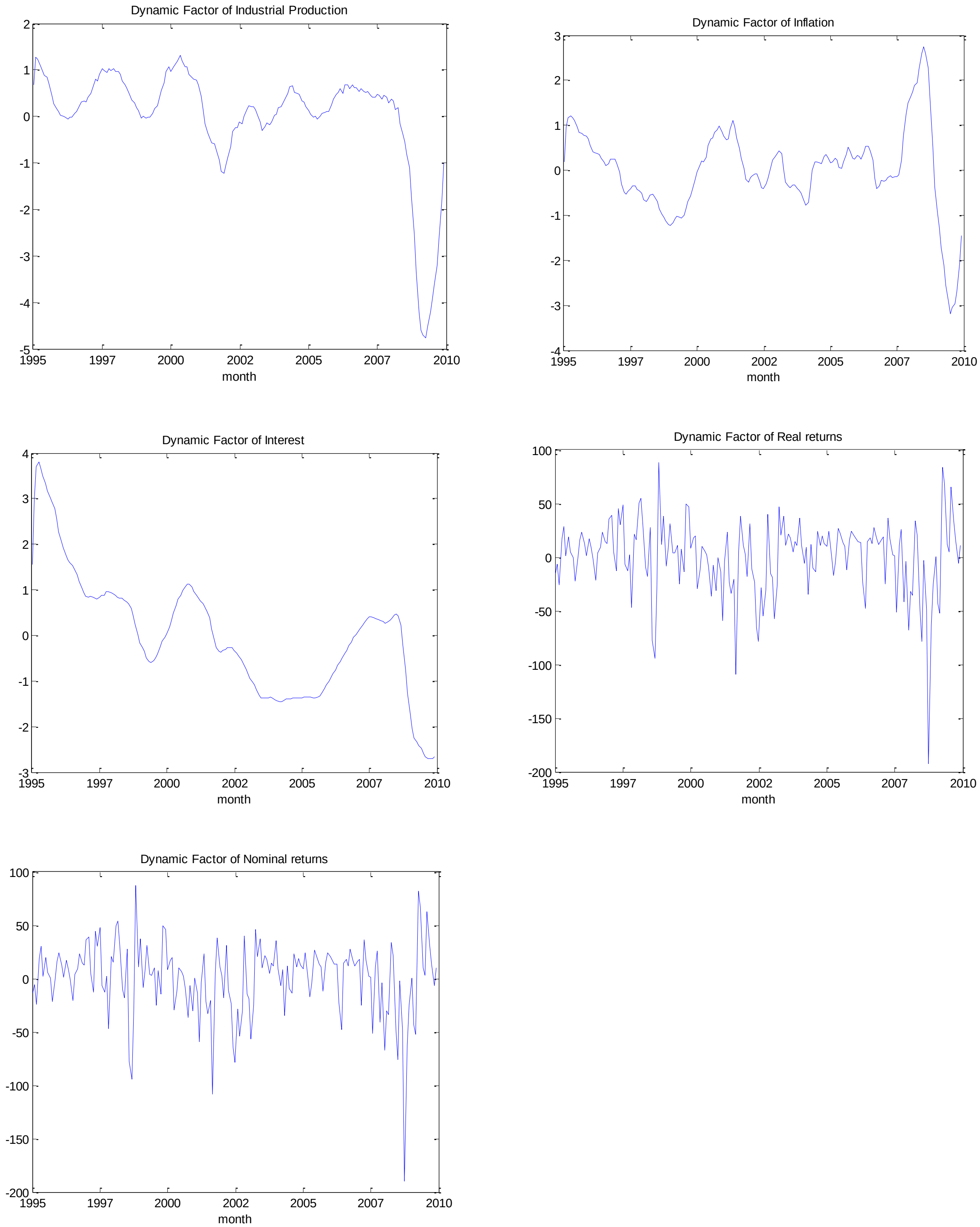
Figure 4.1: Dynamic Global Factors



Notes: Figures plot the five dyanimc global factors for industrial production, inflation, short-term interest rates, real returns and nominal returns over the period of 1995-2009, respectively.

Figure 4.2: Actual and Fitted Values of Variance Share

Figure 4.2.1 Figure 4.2.2

Notes: Fitted values of variance share refers to the share esitamted from the regression of the variance share of global factor for real returns on those for industrial production, inflation and short-term interest rates. The actual values refers to the variance shares of global factor for the real returns based on Bayesia dynamic factor analysis. Figures 4.2.1 and 4.2.2 plot the two regression results for pooled countries and developed countries, respectively.